Knowledge-Based Design Guidance System for Cloud-Based Decision Support in the Design of Complex Engineered Systems

Abstract

The automation and intelligence highlighted in Industry 4.0 put forward higher requirements for reasonable trade-offs between humans and machines for decision-making governance. However, in the context of Industry 4.0, the vision of decision support for design engineering is still unclear. Additionally, the corresponding methods and system architectures are lacking to support the realization of value-chain centric complex engineered systems design lifecycles. Hence, we identify decision support demands for complex engineered systems designs in the Industry 4.0 era, representing the integrated design problems at various stages of the product value chain. As a response, in this paper, the architecture of a Knowledge-Based Design Guidance System (KBDGS) for cloud-based decision support is presented that highlights the integrated management of complexity, uncertainty, and knowledge in designing decision workflows, as well as systematic design guidance to find satisfying solutions with the iterative process "formulation-refinement-exploration-improvement". The KBDGS facilitates diverse multi-stakeholder collaborative decisions in end-to-end cloud services. Finally, two design case studies are conducted to illustrate the proposed work and the efficacy of the developed KBDGS. The contribution of this paper is to provide design guidance to facilitate knowledge discovery, capturing, and reuse in the context of decision-centric digital design, thus improving the efficiency and effectiveness of decision-making, as well as the evolution of decision support in the field of design engineering for the age of Industry 4.0 innovation paradigm.

Keywords: complex engineered system design, decision support, design guidance, complexity management, uncertainty management, knowledge management

Glossary

CPS	Cyber-Physical Systems
PSS	Product-Service Systems
CPPS	Cyber-Physical Production Systems
CPSS	Cyber-Physical-Social Systems
S+PSS	Servitization and Product-Service Systems
CPPSS	Cyber-Physical Product-Service Systems
KBDGS	Knowledge-Based Design Guidance System
CBDS	Cloud-Based Decision Support
PEI-X diagram	Phase-Event-Information X diagram
CDK closed-loop guidance	Concept-Decision-Knowledge closed-loop guidance
FREI	Formulation-Refinement-Exploration-Improvement
HRRS	Hot Rod Rolling System
NMSs	Networked Manufacturing Systems

1. Introduction

A decade ago, the need for disruptive change in the manufacturing sector emerged, driven by the need to meet customers' individual requirements quickly and cost-effectively [1]. This event triggered the Industry 4.0 initiative, first in Germany in 2011 and then worldwide [2]. The Smart Manufacturing Initiative in the US, Made in China 2025 in China, Smart Industry in the Netherlands, Future of Manufacturing in the UK, and Manufacturing In-novation 3.0 in South Korea are some of many Industry 4.0 initiatives [3-5]. From an engineer's perspective, Industry 4.0 refers to smart data processing for more competitive manufacturing, virtualization, and autonomous decisions for real-time intelligence and smart actions, servitization and new business models, smart design, and creation and use anywhere and at any time. As shown in Figure 1, Industry 4.0 has been happening in four overlapping cycles [6]. In the first cycle, Industry 4.0 building blocks were created defining generic architecture models for *Cyber-Physical Systems (CPS),* creating foundations for the architectures of cloud manufacturing and the associate processes to operate on. The second cycle with the more mature adoption of Industry 4.0 building blocks created the foundations for cloud manufacturing architectures to deliver product-service bundles through the *Servitization and Product-Service Systems (S+PSS).* These bundles were required for companies to grow into the Industry 4.0 technology landscape that was created. In the third cycle, new opportunities for value creation from digitization and data, new data-driven business models, and the integration of the supply chain into horizontal *Cyber-Physical Production Systems (CPPS)* will become a paramount challenge facing industry at large. Lastly, in the fourth cycle, the anticipated development over the next five years is a transition from digital silos into holistic decentralized, end-to-end ecosystems where value chain-centric complex engineered systems design guided by knowledge and decision support will lead to a new understanding compared with what we know today.

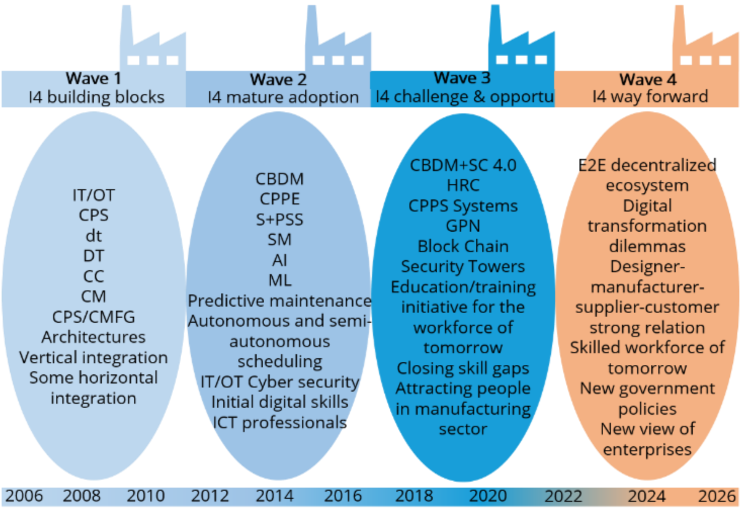

Figure 1. Industry 4.0 Roadmap [6]

It can be seen in the Industry 4.0 roadmap, as shown in Figure 1, that with the mutual development and integration of different enabling technologies, a holistic solution over the complex engineered systems design lifecycle value chain is gradually being recognized and accepted by more scholars and enterprises to address the trade-offs between theoretical concepts and policies in different countries [7, 8]. As shown in Table 1, we present some typical system concepts and features of complex engineered systems in the context of Industry 4.0. In realizing the value-chain centric complex engineered systems lifecycle, the proposed concepts promote the development of design engineering and its technical integration with different disciplines to strengthen the decision support scheme's integrity in different domains. However, in the Industry 4.0 era, the vision of decision support for design engineering is still unclear, and the corresponding method and system architecture lack the support to realize industrial applications [6, 9-11]. With this in mind, this paper proposes the architecture of a Knowledge-Based Design Guidance System (KBDGS) for achieving cloud-based decision support in complex engineered systems design. In the KBDGS, three main functional modules give full play to the integrated management of complexity, uncertainty, and knowledge in value-chain centric complex engineered systems design, based on the concept-decision-knowledge closed-loop guidance method [12] and decision process modeling leveraging the PEI-X diagram [12, 13]. The potential application of the KBDGS goes beyond complex engineered system design, such as environment monitoring, urban intelligence, production intelligence, healthcare, education, and other dynamic social systems, see Figure 2. This paper implements the KBDGS architecture in a computational platform and provides a design guidance method, namely "Formulation-Refinement-Exploration-Improvement" (FREI). The main contribution is to facilitate knowledge discovery, capture, and reuse in the context of decision-centric digital design, thus improving the efficiency and effectiveness of decision-making in value-chain centric complex engineered systems design.

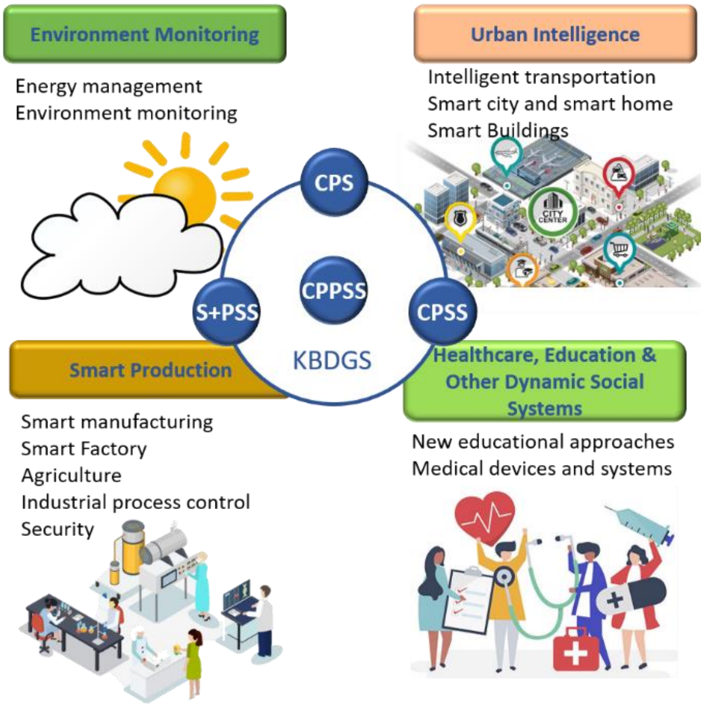

Figure 2. Potential application of KBDGS to different complex systems [14-17]

The remainder of this paper is organized as follows. In Section 2, a critical literature review is conducted to clarify this paper's research gaps and contributions. In Section 3, decision support demands in complex engineered systems design are identified. As a response, the architecture of the KBDGS is defined in Section 4, which refers to the relevant functional frameworks and associated methods for managing complexity, uncertainty, and knowledge. Additionally, the design guidance procedure for implementing the KBDGS is provided. In Section 5, two industrial applications are illustrated. The closing remarks and the future work of the proposed methods are given in Section 6.

Table 1. Concept comparisons of typical complex engineered systems in the Industry 4.0 era

Concept	Major characteristic	Supporting technology	Major research	Refs.
Cyber-Physical Systems (CPS)	• Fusion of physical and virtual systems in manufacturing • Cloud-based numerical control • AR-enabled real-time visibility • Multi-scale dynamic manufacturing processes	• Radio frequency identification device technology • Control system as a service • AI/Knowledge-based design decision-making • IoT-enabled data collection	• IoT-based CPS environment • CPS-enabled smart machine tools/smart factory • Cyber virtualization modeling • Standardization and reference architecture	[3-5, 11, 15, 18]
Cyber-Physical Production Systems (CPPS)	• Intelligent and autonomous interactions of CPS objects • Integration of physical resources as adaptive, secure, and on-demand manufacturing services • Value-added services for design and manufacturing • Value-chain-oriented view of the product and production system lifecycle	• Information and communication technologies • Service-oriented architecture • Knowledge-based design decision-making • Smart scheduling and control • Semantic Web Technologies • Model-driven systems engineering	• Machine scheduling in smart factories • Energy consumption monitoring • Digital twin-based architectural framework • Information modeling and integration of multi-disciplinary engineering • Product and production systems design	[16, 18-21]
Cyber-Physical-Social Systems (CPSS)	• Integration of humans, computers, and the physical environment • Extends CPS to the social domain and features human participation and interaction • Human-centric computation services	• Seamless migration technologies of heterogeneous network • Cloud-based decision support • Context awareness and management • Human-computer interaction • Social computing	• Recommendation based on the social network • CPSS design and modeling • Cloud environment support • Dynamic social relationships learning • Distributed decision-making • Architecture platform	[17, 22-24]

Servitization and Product-Service Systems (S+PSS)	• Value chain reconfiguration for manufacturing service • Unique combination of products and services • Integration and configuration of design and manufacturing resources	• AI/Knowledge-based design decision-making • Service-oriented design • Internet of Things • Virtualization • Context awareness and management	• Mass customization • Service-oriented business models • Value-driven development of product and service • Design, evaluation, and operation methodologies	[7, 14, 25-27]
Cyber-Physical Product-Service Systems (CPPSS)	• Implementation of cyber-physical and servitization technologies in the lifecycle • Value chain-added services for stakeholders	• PSS and CPS technologies • AI/Knowledge-based design decision-making • Cloud services • Semantic Web Technologies	• Lifecycle management of product and service • Design, evaluation, and operation methodologies • Architecture platform	[3, 16, 21]

2. Literature Review

To clarify the research problems in this paper, this section focuses on reviewing and analyzing the current major research. Section 2.1 points out the design approaches of typical complex engineered systems represented by CPS, PSS, CPPS, and CPPSS in the Industry 4.0 era. Section 2.2 gives decision support characteristics for the new design paradigm. Finally, Section 2.3 identifies the research gaps of existing studies and provides this paper's corresponding research contributions.

2.1. Design Approaches of Typical Complex Engineered Systems in the Industry 4.0 Era

Various design methodologies support the development of CPS, CPPS, PSS, and CPPSS as typical complex engineered system designs in the Industry 4.0 context. For instance, Vasantha and co-authors [26] provided a review of PSS design methodologies. This paper explains the relevant approaches based on the three aspects of knowledge, value, and integration through the comparative analysis of numerous existing studies.

- *Knowledge-based approach*. In the knowledge-driven approaches, a variety of functions are realized in designing CPS/CPPS/PSS/CPPSS regarding obtaining and reusing knowledge in design, such as the predictions of disruptions and consequences [21] as well as stakeholders' preferences [28] and the enhancement [29], customization [28], and evaluation [28, 30] of decision-making processes, combining multiple methods to give decision support [31], system evolution [32], and ontology-based service selection [33]. Despite the various functions realized in knowledge-based approaches, there has not been a clear functional vision of decision support for complex engineered systems design. Most authors connect a cyber system with a physical system or synthesize the production and service process. Still, limited decision support is given to managing the whole cyber-physical product-service system regarding complexity and uncertainty management. There is also a lack of knowledge management for different scenarios of complexities and uncertainties as well as exploring design options. Moreover, when leveraging new technologies, the design methods described in the literature incorporate emerging technologies such as cloud computing and the IoT to support the existing framework, rather than systematically innovating and speculating about design concepts to support future technologies.
- *Value-driven approach*. In the value-driven approach, the key challenges and contributions are for designers to develop key performance indices (KPIs) to assess the value in multiple phases along with the PSS and quantify the qualitative and incomplete information to support decision making. Bertoni and co-authors [27] focused on the methodological guidance and tools for value-driven PSS designs, such as knowledge enablers for decision making in optimal PSS planning or early value-based design exploration with knowledge maturity to enhance trade-off analysis in service-oriented design configurations. Thomsen and co-authors [34] proposed a value-maximizing design method and optimized aero-engine component living decisions in a PSS by integrating manufacturing and maintenance alternatives. Mourtzis and co-authors [35] presented an approach for PSS evaluation using KPIs values, which could be extended to all lifecycle phases, taking into account the customers' perception of value. Sakao and Lindahl [36] provided a value evaluation method for designing a PSS with the potential to replace a customer utility analysis. Rondini and co-authors [37] proposed an engineering value assessment method for PSS design that guided the identification of trade-offs in the decision-making through an importance-performance analysis. The value-driven approaches assume that some KPIs or utility functions can reflect the value variation in a PSS accurately. The stakeholders in all departments or phases of a PSS share common interests and accept certain tradeoff scenarios. The management of the complexity and uncertainty in a PSS is through quantifications and simplifications by assessing activity value changes. Cyber-physical systems are not discussed in the value-driven approaches. Design automation based on new technologies such as cloud computing and real-time data collection and processing (from terminal equipment) has not focused on research and discussions.
- *Integrated design approach*. The integration here is a relatively broad concept, including the integration of multiple perspectives [38], stages [39], and stakeholders' or participants' interests [39] or methods [40, 41]. Costa and co-authors [38] discussed the models in service design, PSS, and the integrative PSS approach, and they proposed a design method built on Service-Dominant logic, integrating the human-oriented perspective with an organizational network-oriented perspective. Garetti and co-authors [39] discussed lifecycle simulation as a new approach for achieving sustainability through the

integration among all participants in a lifecycle. Bertoni and co-authors [40] integrated cost engineering into the PSS design to estimate the lifecycle cost of PSS hardware at a conceptual design stage. Andriankaja and co-authors [41] proposed an integrated method to design the PSS life cycle and the configuration of the PSS value network based on the extended functional analysis approach. These integrated approaches help manage the PSS's complexity more flexibly by bringing insight and expertise from different domains and managing the process chain dynamically. However, these approaches lack guidelines to integrate, discover, and reuse knowledge in different fields in a systematic and organized way.

2.2. The Characteristics of the Decision Support in the Context of Industry 4.0

Decision support is an essential part of design engineering. Marcus and Juan [42] surveyed smart design engineering, summarizing and highlighting the value of decision-support in different design processes. Hoffmann and co-authors [8] also conducted a survey of decisions to consider complexities, uncertainties, ambiguities, and dynamic environments in the Industry 4.0 context. Based on our literature review and the concepts listed in Table 1, we summarize the major characteristics of decision support in the Industry 4.0 age as follows.

- *Knowledge-based decision support*. Knowledge management and knowledge-based decision support are much more emphasized in Industry 4.0. The traditional domain knowledge and domain-independent calculation and analysis should be integrated dynamically to support decision-making in the new age. Burggräf and co-authors [43] introduced the role of knowledge-based systems (KBS) by reviewing knowledge-based problem-solving in physical product development. The authors hold that a decision support system (DSS), as a subdomain of KBS, focuses on calculation and analysis, whereas KBS focus on the knowledge and data adaptable to the production integration of complex products and processes in an uncertain environment. Umeda and co-authors [44] presented a lifecycle development framework for integrating knowledge of products and processes. The framework contributed to life cycle option selection. Xu and co-authors [45] focused on the knowledge evolution in product lifecycle design and manufacturing. Agostinho and co-authors [46] reviewed the knowledge and model-driven technology used in sustainable networked enterprises' information systems built on dynamic decision support enablers. Designers need to manage various complexities and uncertainties in a CPPSS based on evolving but still limited knowledge. Therefore, the designers face the challenge of designing a knowledge-based decision support system considering the tradeoffs among versatility, customizability, and robustness.
- *Artificial Intelligence (AI) and Big Data-driven decision support.* AI and big data technologies provide a vast number of opportunities for designers to manage a larger scale and a wider range of complexities and uncertainties. Duan and co-authors [47] discussed AI techniques for decision-making in the big data era and offered 12 research propositions to advance knowledge about maximizing the benefit of new-generation AI systems. Kheybari and co-authors [48] provided an overview of applications of the analytic network process widely used in multicriteria design and manufacturing systems. Ding and co-authors [49] surveyed large-scale decision-making based on AI applications. Li and co-authors [50] reviewed big data technologies used for different stages of the product lifecycle. A subsequent challenge is determining how the systems based on AI and big data technologies provide decision support when data is incomplete, inaccurate, or has various qualities in different circumstances. Design guidance accommodating every situation is needed whether big data is accessible or missing, accurate or inaccurate, complete or sparse, etc.
- *Cloud service for decision support*. Cloud service allows designers to realize real-time analysis and insight generation, which largely improves the scale and efficiency of knowledge management in decision-making. Terziyan and co-authors [51] gave a service-oriented framework, patented intelligence (Pi-Mind), to augment the axioms of decision rationality. Ahmed and Majid [54] reported agent-based problem-solving techniques for cloud service composition as well as a survey on agent-based Petri Nets modeling. Bendul and Blunck [52] proposed a design decision classification framework for a combination of centralized and decentralized decision strategies, as well as guidance for production system design. Theorin and co-authors [53] proposed an event-driven line information system architecture for informed and timely cloud service decisions. Shahin and co-authors [54] proposed a cloud-based Kanban decision support system by integrating Lean practices and Industry 4.0 intellectual technologies. Babiceanu and co-authors [55] surveyed virtualization and cloud-based services for CPS, as well as the utilization of big data analytics for manufacturing operations that enable timely and accurate insights. The challenge of applying cloud service in decision support is designing an architecture that supports the easy implementation and customization of different design guidance systems.
- *Other characteristics*, such as decentralization [52], interoperability [56, 57], virtualization [55], real-time response [3-5, 11, 15, 18], modularity [4, 42, 58], and inclusive and adaptive new-technology [2], endow the decision support in the new age with unlimited possibilities.

However, for this relatively new domain, the decision support in the CPPSS along with the convenience and opportunities brought by new concepts and technologies, there are risks [59], confusion [6, 9-11], uncertainties, and wastage to be managed and overcome. Those challenges are not only brought by new demands but also come out with the utilization of new technologies. In addition to giving decision support to designers for each particular problem, the functionality of the decision support for complex engineered systems needs to be envisioned and clarified. In addition, in the era of Industry 4.0, when the division of disciplines is highly refined and domain knowledge is difficult to generalize, researchers can easily fall into the trap of focusing on a specific viewpoint while ignoring the possibility of understanding, planning, and managing one complex system from different perspectives. Therefore, it is necessary to identify and fill research gaps in response to these challenges to enrich and guide future research about decision support for complex engineered systems.

2.3. Research Gaps and Contributions

By investigating the design approaches and decision support characteristics of typical complex engineered systems such as CPS, PSS, CPPS, and CPPSS in the context of Industry 4.0, it has been found that the perspective of design engineering decision support in the new industrial paradigm is not yet clear and well addressed, for the following reasons:

- *Gap 1: The lack of a clear functional vision of decision support for complex engineered systems design in the Industry 4.0 context*. Although the complex engineered systems represented by CPS, PSS, CPPS, CPPSS, etc., have huge advantages and the inevitable trend of Industry 4.0, as presented in Table 1 and Section 2.1, there are few general flexibility methods to support complex engineered systems design. Most of them focus on the design paradigms of CPS, CPSS, and PSS individually. Research about decision support for the field of design engineering emphasizes the improvement of the decision model itself, neglecting many dilemmas in decision process management, such as synthesizing different levels of decision activities in system design, representing the relationship between products, decisions, and knowledge, as well as defining an extensible functional framework of decision support in the context of the Industry 4.0 era. Hence, more attention should be given to identifying decision support functional demands in complex engineered systems design.
- *Gap 2: The lack of methods and frameworks for decision support to integrate managing complexity, uncertainty, and knowledge in complex engineered systems design*. Section 2.1 points out that different design methods exist in complex engineered systems design, such as CPS, PSS, CPPS, and CPPSS in terms of knowledge, value, and integration. The essence of these methods is derived from the impact of the new industry 4.0 design paradigm on system design complexity and uncertainty. Multi-dimensional complexity and multi-factor uncertainty involving the coupling and interaction between different system domains and decision problems for different disciplines can seriously affect the final product's performance and quality. Especially in Industry 4.0, the dynamic and variable demands increase the complexity and uncertainty of decision-making by different stakeholders in the realization of engineered systems and put forward higher requirements for the adaptability and flexibility of the decision-making process. Looking back at the trends and characteristics of decision support identified in Section 2.2, it is not difficult to find that knowledge-based decision support has become or is becoming a significant way to solve the dilemmas of decision support at present and in the future. Unfortunately, no systematic methods and frameworks effectively integrate complexity, uncertainty, and knowledge to support decision-making with the new design paradigm.
- *Gap 3: The lack of system architecture and a relevant design guidance approach to implementing cloud-based decision support*. As described in Section 2.2, it can be found that many studies have pointed out that cloud-based decision support is becoming an important foundation for the Industrial 4.0 design paradigm with connectivity as the main feature. Although numerous feature-rich decision support systems or tools already exist, there is still a lack of cloud-based decision support systems for the value-chain centric complex engineered systems design lifecycle. In fact, the relevant research described in Section 2.1 also points out the importance of being value-driven in the new design paradigm. Achieving this purpose requires the clarification of the salient features of decision demands for the complex engineered systems design and defining flexible system architecture, increasing designers' ability to understand and predict the process behaviors of the decision-making process, and improving the efficiency and effectiveness of decision-making for different stakeholders.

We propose the architecture of a Knowledge-Based Design Guidance System (KBDGS) to address the aforementioned gaps for achieving cloud-based decision support in value-chain centric complex engineered systems design. The new contributions contained in this paper are summarized as follows:

- *Contribution 1:* We define the decision support demands in the design of complex engineered systems based on the three aspects of complexity, uncertainty, and knowledge, which provide a foundation for addressing the decision support challenges of design engineering in the context of Industry 4.0, as described in Section 3. This is meant to address Gaps 1 and 2.
- *Contribution 2*: We present three frameworks of the main functional modules in the KBDGS for the integrated management of complexity, uncertainty, and knowledge in value-chain centric complex engineered systems design based on the approaches of concept-decision-knowledge closed-loop guidance and decision process modeling via leveraging the PEI-X diagram, as described in Section 4.1-4.3. This is meant to address Gap 2.
- *Contribution 3*: We implement the KBDGS architecture in a computational platform and provide a design guidance method, namely “Formulation-Refinement-Exploration-Improvement” (FREI), which enhances knowledge discovery, capture, and reuse in the context of decision-centric digital design, as described in Section 4.4. This is meant to fill in Gap 3.

3. Decision Support Demands of Complex Engineered Systems Design in the Industry 4.0 context

Through the above literature review and research gaps, it can be found that complexity, uncertainty, and knowledge represent the decision-making characteristics of the major design problems of complex engineered systems at various stages of the product value chain in the context of Industry 4.0. Thus, this section focuses on identifying decision support demands based on these three aspects to fill the above mentioned research gaps.

3.1. Complexity

- *System complexity*: Driven by various emerging technologies, the design complexity of physical systems has become increasingly prominent. Some typical system complexity characteristics, including multifunctional system modules and the multi-scale integration of the mechatronic and cyber-physics system, put forward more flexible decision support requirements [20, 22, 60, 61]. For example, networked manufacturing systems involve sequential and concurrent design mechanical systems and control systems, which influence the evaluation criteria for different optimization goals of decision-makers in the early design stage, such as accounting for being diagnosable, controllable, and cost-effective [57, 62]. Similarly, integrating multi-disciplinary design, such as materials, the manufacturing process, and system products, is also involved [56]. Due to the consistency of system design based on decision-making, the primary challenge of complexity management for decision support is a system's flexible representation with significance for different stakeholders to identify the design space that affects decision results.
- *Design complexity*: Design complexity stems from the inherent complexity of systems that request various design methodologies to meet dynamic and diverse requirements [14, 30, 63]. This is reflected in some specific design aspects, such as integration, sustainability, modularity, and being multi-scale [4, 42, 58]. This is consistent with the requirement-oriented design principles of traditional products [64]. For example, the definition of material property models at different scales is considered in networked manufacturing systems design [3, 56]. However, as products and manufacturing systems develop toward intelligence, some new design requirements follow one after another, including intelligent design driven by data, digitization, and value [3, 4]. Therefore, the challenge of design complexity for decision support is reflected in the adaptability and expansibility of the analysis and synthesis of data, information, models, and knowledge. For example, networked manufacturing systems design has to reuse and generate a large amount of information such as the parameters, models, data results, etc.[62]. The efficient organization and discovery of reusability knowledge can effectively improve the quality of decision-making [45].
- *Process complexity*: Process complexity affects the design cycle implementation and sustainable development of products and systems, as embodied in the coupling of process decision problems at different levels [12, 65]. For example, the decision space of different stages and modules in networked manufacturing systems design is different in that relevant data, information, and model knowledge integrate upstream and downstream problems into the design, and human experts decide to take the best action to dynamically adjust the design process and strategy considering the interrelated factors to further the clarity of goals [56, 57]. Different decision processes and strategies produce different design results [66]. The process complexity is at the mercy of integrating and utilizing information flow in different nodes to better support decision-making. The challenge of process complexity lies in the flexible and scalable representation model of the decision process and process design mechanism for the effective organization and management of a large amount of design-coupled information.
- *Organizational complexity*: Even for complicated design or advanced technical support, human participation and decision-making are indispensable [23, 24, 51]. For example, as decision-makers, designers need to clarify the design concept, define the design space, identify the goal priorities, judge the satisfying solution, and determine a series of decision behaviors [14, 51, 60]. Although AI technology can enhance the abilities of computers to make certain decisions, so far, its capabilities have been limited [5, 42]. Furthermore, the organizational dimension also involves the trade-offs between different stakeholders and the embodiment of value. For example, policymakers, industrialists, consultants, researchers, and others may have opportunities to participate in decision-making activities at various levels with different system roles (i.e., system actors, system designers, and system influencers) [38, 67]. Hence, the challenge of decision support arising from organizational complexity focuses on reflecting the corresponding human roles at the decision level, that is, the function identification and division of human designers in decision-making.

3.2. Uncertainty

- *Uncertainty in problem modeling*: The model-based realization of complex engineered systems with notable Industry 4.0, especially in simulation-based design, involves the problem modeling's internal and external uncertainty sources [43, 68]. The internal factors refer to the system model's variabilities due to simplifying assumptions and idealizations, limited experimental data considering cost and computations, etc. [17]. The external factors include decision preferences and cognition influencing the demands and expectations of the design, such as user satisfaction diversity, individual preference differences, design constraints for sustainability, as well as rapid changes in product quality, production capacity, or inventory caused by specific emergencies in the manufacturing or supply chain network [42, 69]. For example, in multistage manufacturing systems design, there is a need to account for many sources of variation and uncertainties as well as some unpredictability of a mechanical system known as the model parameters due to incomplete knowledge of model parameters and the inputs and sensing parameters (sensors) in the process [62]. As a result, many challenges for decision support arise in identifying, quantifying, and evaluating uncertainty and primary uncertainty management tasks.
- *Uncertainty in decision process*: Due to the coexistence of various uncertainties in design, the application of existing processes, methods, and tools to manage various uncertainties necessitates a computational environment that enables a system model to integrate the associated information [70]. The traditional design process models, such as the IDEF0, BPMN, and EPC, are unsuitable for describing the uncertainty information in the process chain and its uncertainty transitivity. For example,

multistage manufacturing systems design involves propagated uncertainty as a combination of the unpredictability in the model parameters and the model structure unpredictability in the model chains. Therefore, the challenge is to provide a hierarchical process model with a stronger semantically graphical expression to explicitly depict the values of the parameters interlinked with individual subsystems and the propagation characteristics of the uncertainty in the model and the process chain.

- *Uncertainty in design exploration*: The most desired vision of uncertainty management is to enable the system that is designed to be robust and resilient to emergencies that reflect the adaptive nature of decision-making. This is particularly significant in the design of complex engineered systems in the Industry 4.0 era [69]. For example, the dynamic management of a multistage manufacturing system involves implementing the system's diagnosability and adaptability leveraging extensive design space exploration based on data acquisition from different sensors [62]. Considering uncertainties in design exploration (e.g., incompleteness and inaccuracy system models, decision preferences), designers have to systematically adjust the design space in due time to manage the risks of errors accumulating and propagating during the design of different stages of the process chain [59]. Therefore, the challenge is to explore the influence of uncertainty on system design results and its dynamic propagation characteristics in the decision-making process.

3.3. Knowledge

- *Knowledge classification*: Effective knowledge classification is the premise of knowledge-based decision support [45]. Existing knowledge engineering research usually divides design knowledge into two types: product-related and process-related [71]. Our previous research built on this by supplementing a third type of knowledge, problem-related knowledge, emphasizing a decision-centric design perspective [13]. The reason for this is that the design of physical products and systems can often be regarded as a knowledge-based problem-solving process in which decision-making is an important transformation from information to knowledge [43]. The knowledge of decision-making processes covers human experience and strategies for problem solutions. It is not equivalent to product or process-related knowledge, but rather to knowledge of the specific problem-solving strategy of decisions. Therefore, knowledge classification in decision support is not limited to a single dimension. More knowledge classification perspectives facilitate more flexible and effective decision support, such as content-type (e.g., product-related, process-related, and problem-related) and formal-type (descriptive knowledge and procedural knowledge).
- *Knowledge representation*: The formalization and representation of knowledge has received strong attention in the last few decades [12]. Formal knowledge involves engineering know-what and know-how embedded in documents, manuals, computer algorithms, 3D geometric models, simulation models, and problem-solving routines. [72]. Correspondingly, tacit knowledge that is tied to experiences, rationality, intuition, and implicit rules is considered engineering know-how and know-why. Integrating various aspects of knowledge needs is the development trend of knowledge representation [72, 73], especially in the Industry 4.0 era. Formal knowledge representation is the foundation of realizing reusability and knowledge-driven intelligence [42]. Therefore, the challenge is not the knowledge representation technology itself, but rather the definition of the knowledge terms and the identification of reusable information that can be extensible and adaptable to more flexible decision support.
- *Knowledge capture and reuse*: Identifying appropriate and accurate knowledge demands and reuse behaviors for different individuals, activities, and design objects is a long-term focus of knowledge communities, especially research fields in knowledge management and knowledge-based engineering [72, 74]. Knowledge capture and reuse is the basis for achieving collaborative and integrated decision-making in knowledge-intensive system engineering [71]. It is clarified that ontology-based knowledge representation facilitates semantic retrieval, interoperability, and communication in knowledge sharing [13]. Additionally, the integration of knowledge and computer-aided tools is beneficial to computational decision support, thus enabling knowledge-driven design automation [72]. Therefore, the challenge lies in integrating traditional knowledge service modes and cloud-based decision support with the background of Industry 4.0.

4. Building a Knowledge-Based Design Guidance System for Complex Engineered Systems Design

Design engineering in the Industry 4.0 era presents new challenges for decision support. In response to the decision support demands for managing complexity, uncertainty, and knowledge in the design of the engineered systems identified in Section 3, we propose the architecture of a Knowledge-Based Design Guidance System (KBDGS) for the realization of value-chain centric complex engineered systems design lifecycles, involving various stakeholders (e.g., customer, designer, manufacturer, supplier), as shown in Figure 3. A three-layer functional structure of the KBDGS is defined, including three main available modules: system concept management, decision workflow management, and design knowledge management. Different modules support decision collaboration and knowledge sharing among designers with different roles in the complex engineered systems design value chain via icon-based cloud services. Significantly, the Phase-Event-Information X (PEI-X) diagram proposed in previous work [12, 13] supports the design of decision workflows for complex engineered systems design with different requirements scenarios. The difference is that customizable cloud services with configurable and extensible features (e.g., process modeling, decision problem-solving, post-solution analysis) facilitate better modularity knowledge reuse and sharing through PEI-X diagram icons to manage complexity and uncertainty.

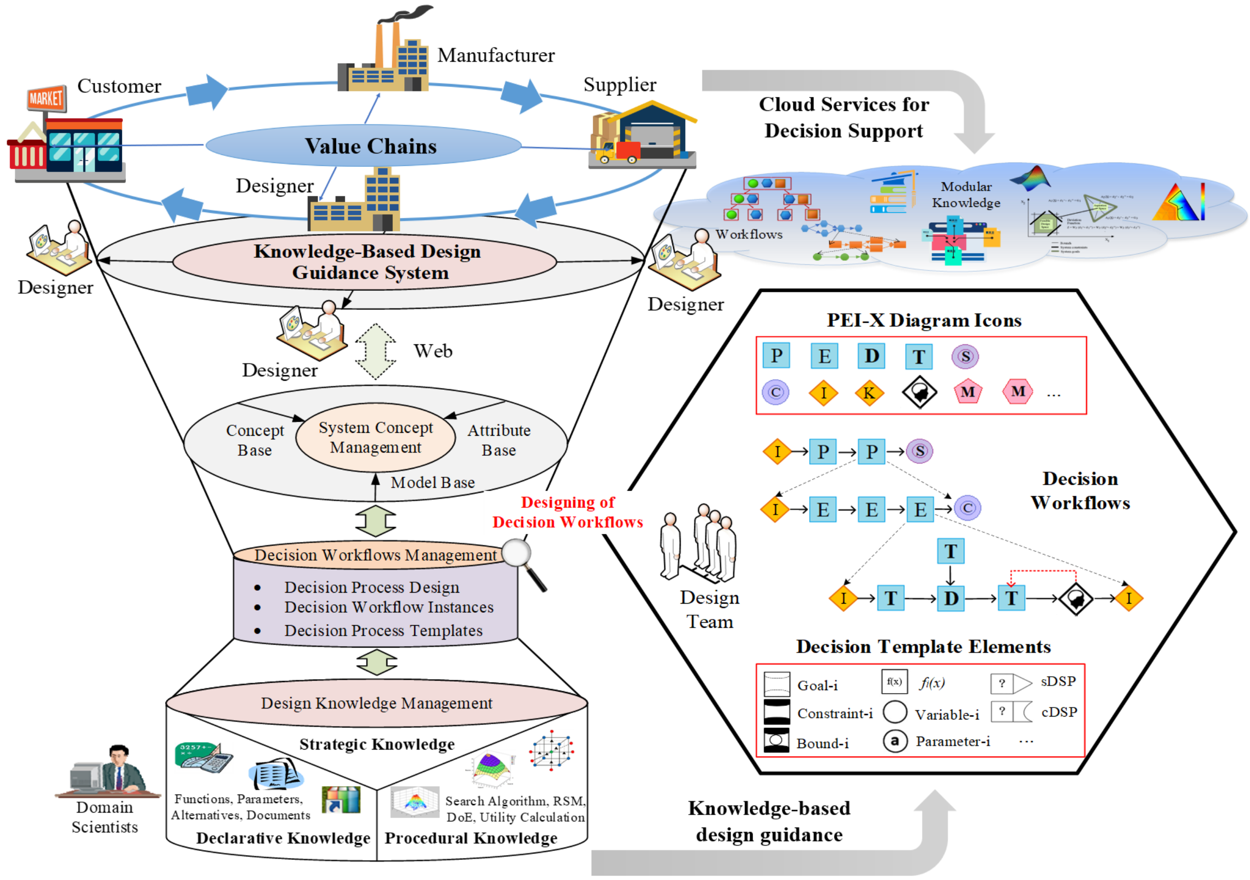

Figure 3. Architecture of knowledge-based design guidance system for cloud-based decision support

4.1. Complexity Management

In the realization of value-chain centric complex engineered systems design lifecycles, the complexity management of decision support involved in different stages corresponding to Section 3.1 is presented for the following solution, namely the "Concept-Decision-Knowledge" (CDK) closed-loop guidance driven by the "Formulation-Refinement-Exploration-Improvement" (FREI) iterative processes, as shown in Figure 4.

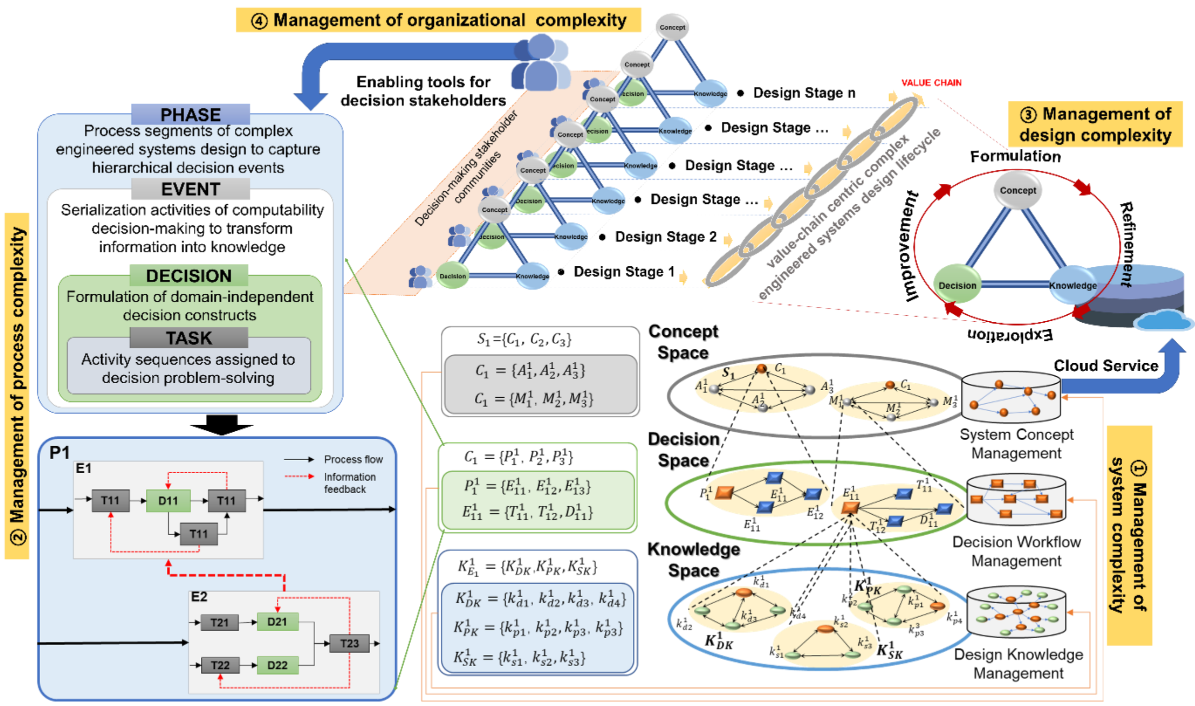

Figure 4. Complexity management of decision-making in design guidance

- *Management of system complexity*: As mentioned above in decision support demands, the challenge of system complexity lies in the flexible representation of design space. The key point is that one needs to consider generalized decision formulation that conforms to different stages of complex engineered system design. For this purpose, we adopt the domain-independent Decision Support Problem Technique (DSPT) proposed by Mistree and co-authors at the University of Houston [75]. The CDK closed-loop guidance is derived based on CK theory [76], in which concept space is the unified representation of product system information in different stages. For example, system information can be denoted as $S_i = \{\sum C_j \,|j = 1 \cdots n\}$, where the system information of different stages is abstracted as C_j, and the total amount of concept space n depends on the design requirements of the specific system for different designers. For example, for a material designer who is concerned only with material properties and the corresponding mechanical performances, the C_j can be identified as material concepts and mechanical concepts. Each concept space is composed of a set of concept attributes and a series of problem-solving models, which are denoted as $C_j = \{\sum A_k, \sum M_g \,|j = 1 \cdots p, g = 1 \cdots q\}$. For example, Figure 4 shows that system $S_1 = \{C_1, C_2, C_3\}$, where each concept is represented as $C_1 = \{A_1, A_2, A_3\}$ and $C_1 = \{M_1, M_2, M_3\}$. In this way, the entirety of the design information consists of different systems, concepts, attributes, and models to form a complex hierarchical network structure, which facilitates the management of the system complexity.
- *Management of design complexity*: The design complexity is reflected in solving the decision problem at different nodes in the above-constructed system network to improve the analysis and synthesis of the data, information, models, and knowledge in the entire network. As shown in Figure 4, each concept C_j in the CDK closed-loop can be identified as a different level of the decision-making process. The solution for each decision node involves different types of knowledge. We develop a FREI solution iterative process for the CDK closed-loop, and its detailed implementation process is explained in Section 4.4. The processes of formulation and refinement in the FREI focuses on the operation of *Concept Space* - *Decision Space* ($C \to D$ and $D \to C$), that is, creating and refining the decision process and its decision space corresponding to each concept (operation $C \to D$). For instance, the identified system concept is denoted as $C_j = \sum(P, E, D, T)$, for which the decision information is transmitted in the process nodes with different granularities (i.e., phase, event, decision, and task), and the coupling information is formulated and refined step by step. The results obtained from different decision-making processes can be fed back to help designers further evaluate concepts and refine the concept space (operation $D \to C$). The processes of exploration and improvement in the FREI focus on the operation of *Decision Space – Knowledge Space* ($D \to K$ and $K \to D$), that is, creating and reusing domain knowledge in the decision process. For example, the event node is denoted as $E = (\sum K_{DK}, \sum K_{PK}, \sum K_{SK})$, where K_{DK}, K_{PK}, K_{SK} represent the declarative knowledge, procedural knowledge, and strategic knowledge, respectively (the details are explained in the knowledge classification of Section 4.3). In terms of the exploration process, the solution process of the identified decision space (e.g., sensitivity analysis, goal clustering, visualization) generates a large amount of new knowledge beneficial to the designer's decision-making (operation $D \to K$). Simultaneously, the newly generated knowledge and the existing knowledge can be captured to realize the reuse of a new round of solution iterations for concept improvement (operation $K \to D$). More details about the CDK closed-loop and FREI solution iterative processes are given in [12].
- *Management of process complexity*: Obviously, the complexities of the system itself and of its design lead to a high degree of coupling and decision process information interaction. In contrast, the existing process modeling methods are mainly focused on the business process in design, and these methods cannot meet the decision support demands for complex engineered system design [12, 13]. The development of the PEI-X diagram is intended to solve this dilemma to improve the efficiency and effectiveness of decision-making by expanding the DSPT palette defined in Ref. [77] and adapting to the decision support demands of Industry 4.0 (as identified in Section 3.1). As a domain-independent decision process model, the PEI-X diagram supports the establishment of hierarchical decision processes. The functionality of each process level (i.e., phase, event, decision, and task) is defined in Figure 4. The interactive manners of the process nodes are defined as vertical interaction patterns (nodes at the same level, e.g., E_1 and E_2) and horizontal interaction patterns (nodes at the different levels, e.g., E_1 and D_{11}) [12]. This profits from the flexible and extensible meta-design (i.e., designing design process) of decision processes that incorporate business processes and scientific computing into the realization of complex systems. Within the CDK closed-loop guidance, the PEI-X diagram represents the implementation processes of specific system concepts required by different stages.
- *Management of organizational complexity*: The management of organizational complexity is reflected in the complex engineered system design team's role assignments, which involve different stakeholders in the value-chain lifecycle that influence product design decisions. In the PEI-X diagram, different roles undertake different decision-making responsibilities. For example, the design team is divided into <system manager, domain expert, engineered designer>. The system manager is accountable for analyzing the requirements of a system and clarifying its design concept. The domain expert is accountable for developing detailed decision processes and formulating appropriate DSP models for a specific design concept, ultimately leveraging domain knowledge to judge the design results' acceptability to provide sufficient decision-making recommendations to refine the concept. The engineered designer is accountable for designing and implementing tasks in a specific decision process and determining the design concept's final attribute values via the identified design activities of robust concept exploration. Cloud-based decision support services can be customized to configure the appropriate knowledge

for a particular role to improve its decision efficiency.

4.2. Uncertainty Management

In the realization of value-chain centric complex engineered systems design lifecycles, different uncertainty sources of concern for this paper are identified in Section 3.2. The corresponding uncertainty management for decision support is presented as the following solution, as shown in Figure 5.

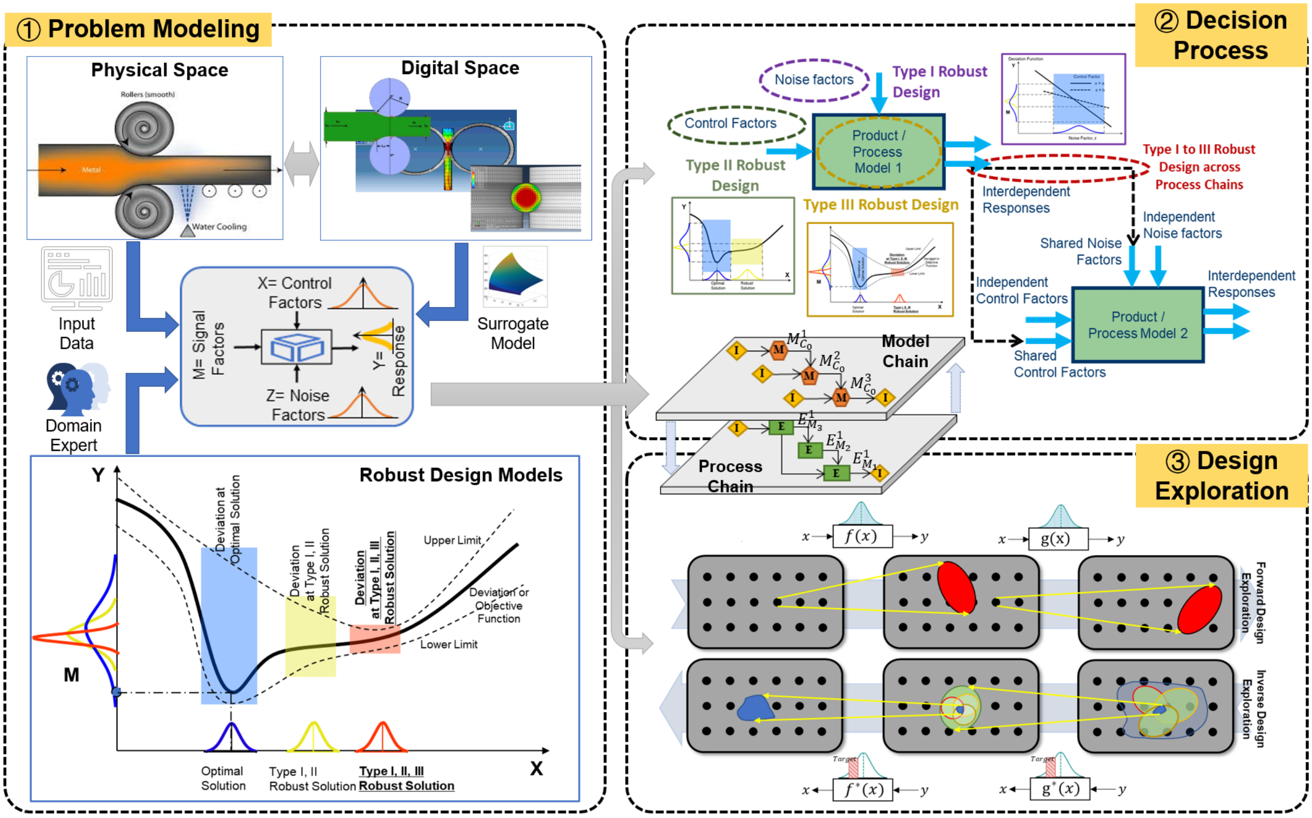

Figure 5. Uncertainty management of decision-making in the design guidance

- *Problem modeling*: The purpose is to realize the identification and quantification of uncertainty. Considering the digital design context, the virtual modeling for physical space and digital space that reflects the characteristics of digital twins has the potential to be applied to the input data collection of problem modeling and the formulation of computational problems based on the surrogate model. The improvement of data quality and algorithmic power is conducive to uncertainty management [68]. However, so far, the intervention of domain experts is still needed to recognize and quantify uncertainty. In previous work [70, 78], three types of robust design methods in realizing complex engineered systems have been analyzed and discussed. In the KBDGS, the factors influencing the system response, including the system model noise, input parameters, model parameters, and model structure, are still recognized as the essential sources of uncertainty and they are defined as the input parameter uncertainty (IPU), model parameter uncertainty (MPU), model structure uncertainty (MSU), and propagation uncertainty (PU). There are four attribute types defined for the simulation model's parameters, covering the control factors, noise factors, the response, and the fixed-parameter. Additionally, the numeric types of parameters need to be specifically described as intervals or discrete values, as shown in Figure 8. Accordingly, the design capability indices (DCI) [79] and the error margin index (EMI) [80] are used to quantify and calculate uncertainty for three relevant types of robust design.
- *Decision process*: The purpose is to realize the management of the uncertainties identified in a complex decision network's propagation process. The influence of the uncertainty on the system itself is considered, and the system model's types need to be defined. Hence, a graphical expression for designing robust design hierarchies is defined, using strong semantics to represent each element's features in the robust design model layer. See Ref. [70] for details. Figure 5 shows that the system model used to describe the relationship between the design requirements and the system parameters is classified into a certain model (pentagon box) and an uncertain model (hexagon box) in the PEI-X diagram. The model chain constructed with multiple system models represents the designer's cognitive process of problem-solving. For instance, a model chain for solving the system concept C_0 is denoted as $M_{C_0} = \{M_{C_0}^1, M_{C_0}^2, M_{C_0}^3\}$, which can be one of or some combination of IPU, MPU, and MSU. The decision workflow is created to solve the corresponding decision problem of the system model. For example,

the uncertainty involved in the model instance $M_{C_0}^1$ is identified as noise factors and control factors, so the Type II robust design method with DCI is adopted to formulate a decision model and solve its design results. In the CDK closed-loop guidance, it is an operation of $C \rightarrow D$. In particular, the parameter attribute types and coupling information in the process nodes and information flow between two nodes need to be further clarified.

- *Robust design exploration*: The purpose is to realize the tradeoff among multiple conflicting goals in the decision-centric robust design and find a satisfying solution (not an optimum solution) that engages the adaptability to the variations and emergencies. Thus, exploring system concepts in the early design stage appears to be particularly essential. For example, the design scenarios of the system concept C_0 involved cover the decision preference (i.e., priority level, weight), uncertainties of decision space (e.g., variability ranges, acceptability of target), and uncertainty types (i.e., IPU, MPU, MSU), etc. Different design scenarios often involve different exploration strategies. Figure 5 shows forward and reverse design exploration strategies according to the interaction between the information flow and decision workflow of problem models, representing the designer's decision process behaviors. The former emphasizes the propagation of parameter information in different model spaces to realize the mapping from a rough design space to a solution space like multi-attribute tradespace exploration [58]. The latter is derived from goal-oriented inverse design while implementing a top-down design process (e.g., mechanical properties are subject to structural properties, see Ref. [81]). The overall design exploration procedure is defined in [59], including robust decision models with DCI/EMI, sensitivity analyses for different design scenarios, and decision space adjustment.

4.3. Knowledge Management

In the realization of value-chain centric complex engineered systems design lifecycles, a significant amount of reusable knowledge needs to be supported appropriately to manage complexity and uncertainty. In the KBDGS, we provide knowledge-based design guidance support based on three aspects: knowledge classification, modeling, and capture and reuse services.

- *Knowledge classification:* Responding to knowledge classification's diversity for identified decision support demands, the knowledge space in the proposed CDK closed-loop guidance consists of declarative knowledge, procedural knowledge, and strategic knowledge [12], which correspond to different decision support scenarios involving instantiation reuse, automatic execution, specific problem-solving, respectively. (1) Declarative knowledge refers to static unstructured knowledge such as document resources, including standards, manuals, and criteria, as well as structured knowledge such as mathematical functions, alternatives, design parameters, and deviation responses. (2) Procedural knowledge refers to dynamic and computability knowledge that can be executed in a computer environment, such as algorithms, analytical procedures, and calculation routines. The procedural knowledge can be packaged into a "black box" by integrating application programs with interrelated drivable templates based on knowledge-based engineering technologies [72], including application and related model programs via instantiating inputs and outputs. (3) Strategic knowledge refers to a series of validated approaches capable of addressing specific design problems, such as the surrogate model development, post-solution analysis, and robust design. In the KBDGS, we emphasize the flexibility and extensibility of knowledge management, so the proposed knowledge classification can ensure the integrity of decision support and better adapt to the updating and evolution of knowledge in the Industry 4.0 context.
- *Knowledge modeling:* Knowledge modeling is the basis for which intellectual capital plays a role in digital design [45]. Ontology is widely used in various application areas that benefit from flexibility, intelligent behavior, semantic interoperability, and expressiveness. In the KBDGS, a design guidance ontology (DGO) is constantly being developed to facilitate knowledge integration and sharing to guide the decision-making process, as shown in Figure 6. Consistent with decision-support demands for knowledge classification, the DGO comprises three dimensions (the upper classes of the ontology): process, product, and problem. The DGO is continually being improved and refined based on different aspects, such as an ontology for meta-design process hierarchies [13], an ontology for systematic design space exploration that integrates decision-centric design problem-solving process [59], and an ontology for uncertainty management in the robust design decision process [70]. In the context of Industry 4.0, the expansion and refinement of the product/system dimension is the focus of the DGO, including the social domain, cyber domain, physical domain, production domain, and service domain. Relevant knowledge in different domains can be represented by the respective domain ontologies [33].

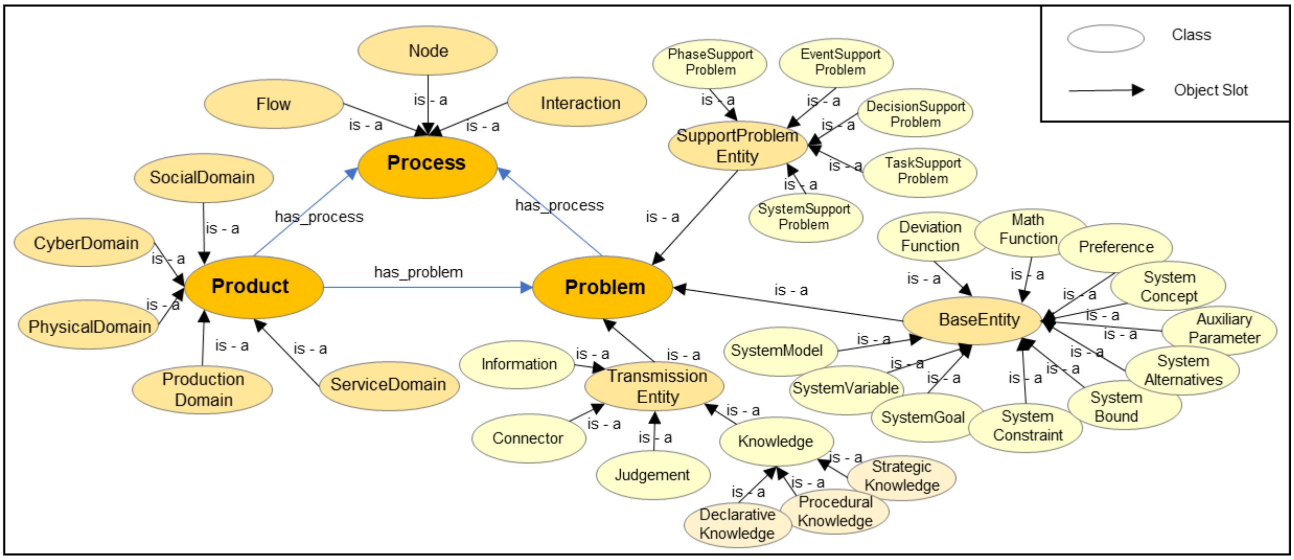

Figure 6. Fragment of design guidance ontology (parts of classes and relationships)

- *Knowledge capture and reuse:* The discovery and capture of new knowledge and reuse are indispensable components for improving the efficiency and effectiveness of decision-making. An icon-based modular cloud service in the KBDGS is adopted to implement executable and reusable knowledge templates to achieve these purposes. So far, we have defined the knowledge icon templates presented in Figure 7 that involve three types of knowledge repositories (corresponding to the knowledge classification identified). Examples include the icons of a mathematical function, model parameters, and alternative options used to capture system models information, the icons of design scenarios, goal priority, weight template, and level template used to capture the decision preferences, the icons of the correlation matrix, the deviation response, the clustering template, and the deviation function template used in the post-solution analysis. A template-based ontological method is presented to support knowledge capture and reuse (see Refs. [13, 59, 70]), which achieves the service application at different stages of the design life cycle with the decision workflow based on icons. Designers can use knowledge modules in the declarative knowledge repository to design and configure the problem model of a selection decision or compromise decision in the DSPT context, and then obtain the corresponding results by instantiating the executable template stored in the procedural knowledge repository. Furthermore, the established strategy knowledge guides the decision-related activities. In the computational environment, modular-based design methods can enhance design flexibility, improve design efficiency, and facilitate a life cycle value chain for different scenarios. More importantly, the knowledge icon is extensible, which is conducive to the integration and application of more functional knowledge.

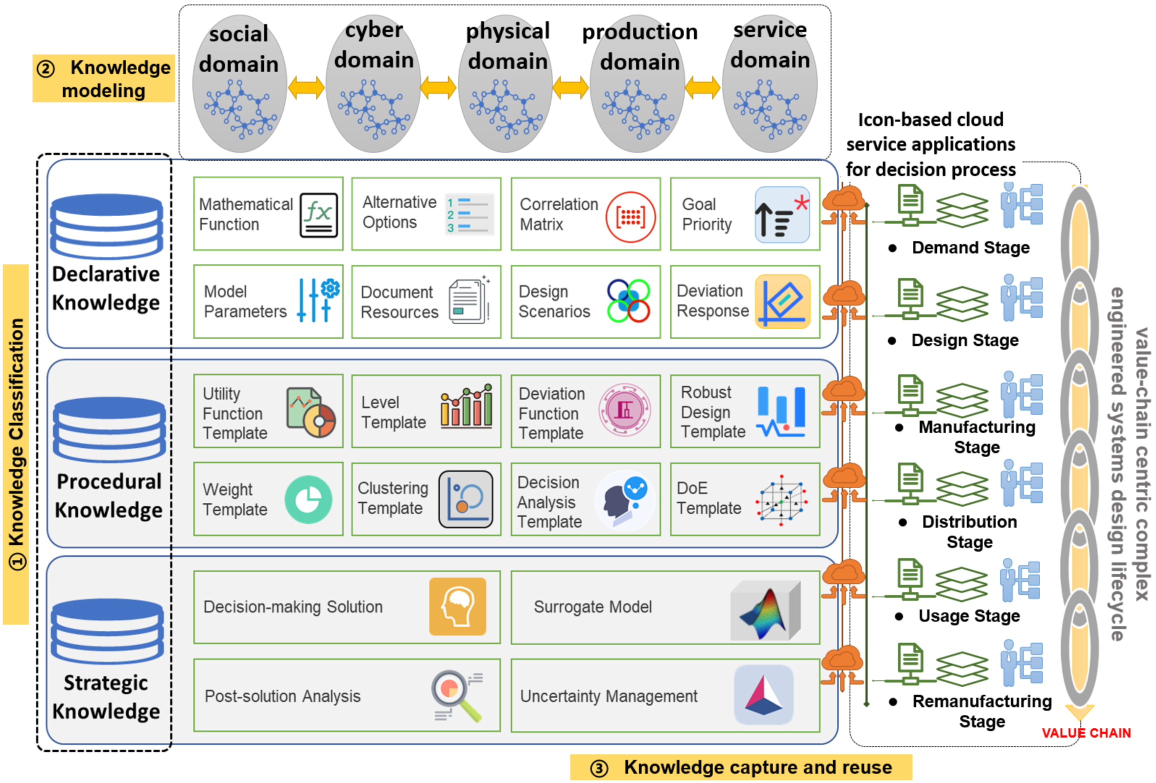

Figure 7. Icon-based knowledge management of decision-making in design guidance

4.4. Implementation of the Knowledge-Based Design Guidance System

Computationally, three vital functional frameworks involved in the KBDGS are defined in response to identified decision support demands in complex engineered systems design. Figure 8 shows the design guidance procedure for the decision-making process, which supports different stakeholders in implementing specific-domain design requirements for satisfying solutions by leveraging the management of the complexity, uncertainty, and knowledge in the KBDGS. The procedure includes six steps following the solution iterative process mentioned in the CDK closed-loop guidance, namely "Formulation-Refinement-Exploration-Improvement" (FREI) [12].

Step 1: *Identification of system concept*. As the starting point of complexity management, the designer's primary task is to determine the system concept for the specific domain design requirements, which may be an initial concept set composed of one or more concepts. Some declarative knowledge (hard information like documentation resources and soft information like empirical knowledge) covering multiple disciplines will provide references for designers to some extent.

Step 2: *Clarity design attributes and models of the system concept*. Given an identified system concept, the design solution consists of design attributes such as the system goal, system variables, and parameters obtained for certain constraints and design scenarios. They are quantifiable representations of an abstract system concept. Different combinations of design attributes may generate different system concepts resulting in different product results. Therefore, a designer needs to clarify the identified system concept's design attributes and the problem model's availability. For the details of problem modeling in CDK closed-loop guidance, see Ref. [12]. Design knowledge is instantiated by existing mathematical functions and reusing the strategic knowledge to develop surrogate models.

Step 3: *Construct the problem-solving model chain*. As mentioned in Section 4.1 and 4.2, the designer's problem-solving strategy can largely influence the design outcome of the system concept. Thus, the base entities in the PEI-X diagram are used to construct the problem model chain, combining the solution strategy of the designer's understanding of the problem (i.e., a certain or uncertain model, and forward or inverse model chain).

Step 4: *Formulation and refinement of decision workflows*. Based on the identified concepts and their model chains, the designer can establish hierarchical decision workflows. The process nodes correspond to different stages' problem-solving of system concepts in complex engineered systems' design lifecycle, detailed in Ref. [12]. The designing decision workflow based on the PEI-X diagram is flexible to capture decision-making process behaviors by continuously refining its hierarchy and interactive information. For more details of the design of decision workflows with uncertainty, see Ref. [70].

Step 5: *Design space exploration*. As an important part of the FREI solution iteration process, design space exploration mainly involves formulating and solving decision models (e.g., compromise DSP [75], selection DSP [77]), the generation and updating of design scenarios, post-solution analysis, and design space adjustment. The detailed guidance procedure for design space exploration is defined in Ref. [59]. The purpose of design space exploration is to extend a designer's abilities to make robust, flexible, and modifiable design decisions and to find a satisfying solution using the tradeoffs between the conflicting goals, and design preferences. For this purpose, it is essential to constantly adjust the design space, and even reconfigure and reformulate the topological structure of the decision process.

Step 6: *Solution Improvement*. A satisfying solution's acceptability does not mean the design ends for a given system concept. In the design lifecycles of complex engineered systems, the design decision guidance involves improving the solutions of system concepts, which refers to further refining design attributes or extending the current concept. Iterative solution processes ensure the integrity of decision-making in the design.

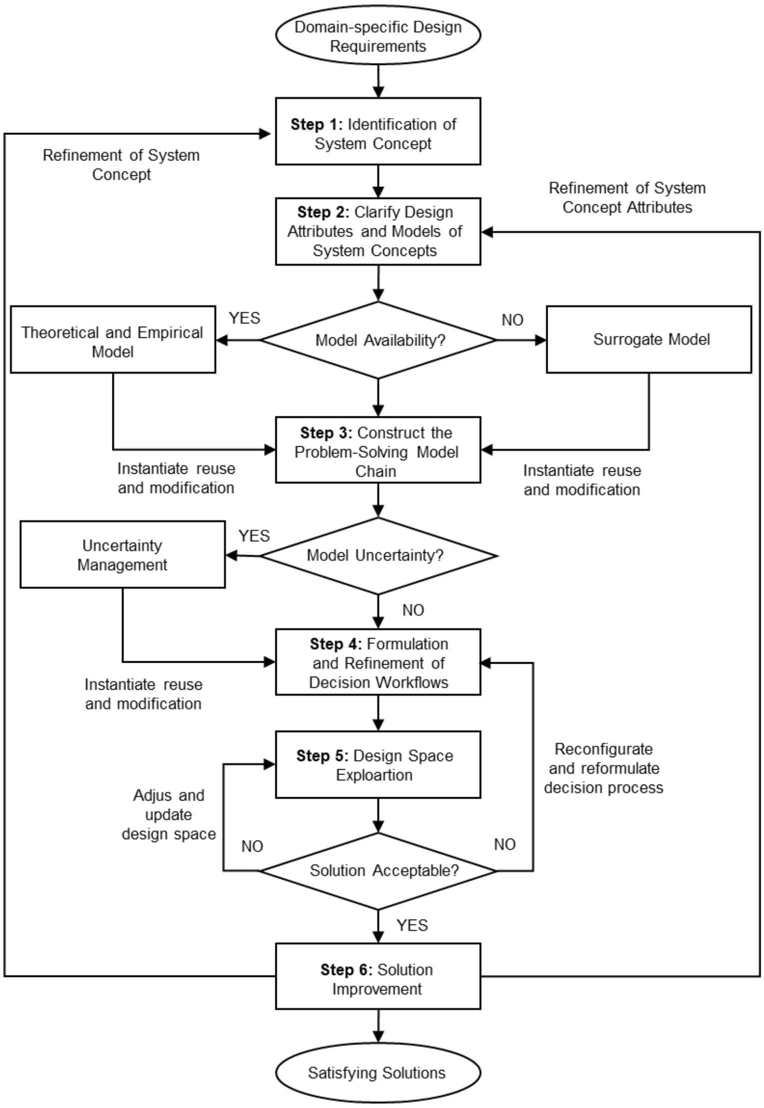

Figure 8. Procedure of design guidance for decision-making processes in the KBDGS

The KBDGS prototype is implemented as a cloud service architecture that facilitates decision support with web browser-based graphical user interfaces (GUI) over the internet, as shown in Figure 8. Different stakeholders in the design lifecycles of the value-chain centric complex engineered systems can remotely access the KBDGS application deployed in the cloud via a browser (e.g., Google Chrome, Internet Explorer), specifically, the knowledge service is defined in Section 3.4, and this knowledge service can be integrated and applied with the “Knowledge” icon embedded in the PEI-X diagram. The constructed decision workflows displayed in Figure 9 include the problem partitioning strategy and the model chain used to describe the system's concept; its corresponding decision workflows are used to solve and explore the identified design problems. The hierarchical, variable-granularity process model and visualization of decision-making problem-solving enable designers to improve the understanding and prediction of process behaviors for different demand scenarios in complex engineered systems design. Various design problems are being applied to the KBDGS, such as multistage manufacturing systems, closed-loop supply chain networks, cyber-physical social systems, etc. Two of these cases are briefly described below.

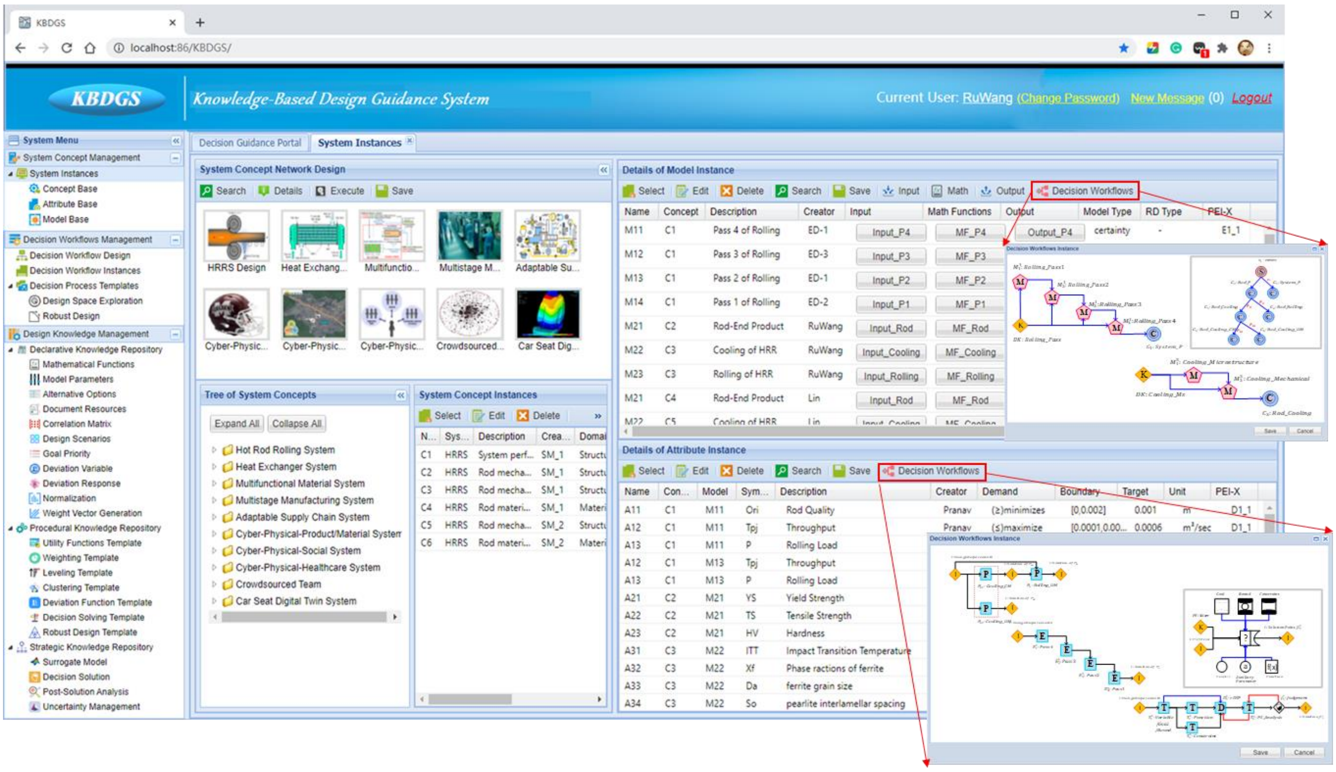

Figure 9. Main GUI of the knowledge-based design guidance system (KBDGS)

5. Case Study

In this section, the efficacy of the proposed architecture is verified, and we apply the developed KBDGS to solve two industry problems, viz., the Hot Rod Rolling System (HRRS) design [56] and the Networked Manufacturing Systems (NMSs) design [62, 82]. The rationale for selecting the former is that we highlight the effectiveness of the KBDGS in the complexity management of HRRS design, especially the CDK closed-loop guidance to support the problem-solving of a given system concept. The latter emphasizes the uncertainty management in the adaptive design of NMSs. We briefly discuss how the decision-related knowledge in these two problems is captured and visualized using an icon-based graphical PEI-X diagram for the information interaction of the decision workflows in the KBDGS.

5.1. Complexity Management Case in the KBDGS: Hot Rod Rolling System Design

The Hot Rod Rolling System (HRRS) is one of the critical segments in multi-stage steel manufacturing processes for which many unit operations are involved [56], as shown in Figure 10. Judging from the integrated co-design of materials, products, and manufacturing processes, the decision support of HRRS design has large amounts of complexity and uncertainty [12, 70]. The manufacturing process steps link the end performances of the steel product and the properties of the material composition at the final and intermediate stages. The decision-makers of steel manufacturing processes should be aware of the design set-points for each unit operation in the plant scale production of steel products in order to realize dynamic management based on cyber-physics. This requires exploring the design set-points and anticipating the results produced by systematic design space exploration [59]. Because of the digital design and manufacturing innovation paradigm and the new product development models/technologies (e.g., sensing technology and cloud-based instant communication as well as sharing technology), the HRRS design also presents many challenges for the co-design of materials, products, and manufacturing processes in the digital era. Some of the core functional requirements for CBDS are defined to address these challenges [56]. As a response, the decision support of the KBDGS for the HRRS design guidance based on the framework proposed in this paper is illustrated.

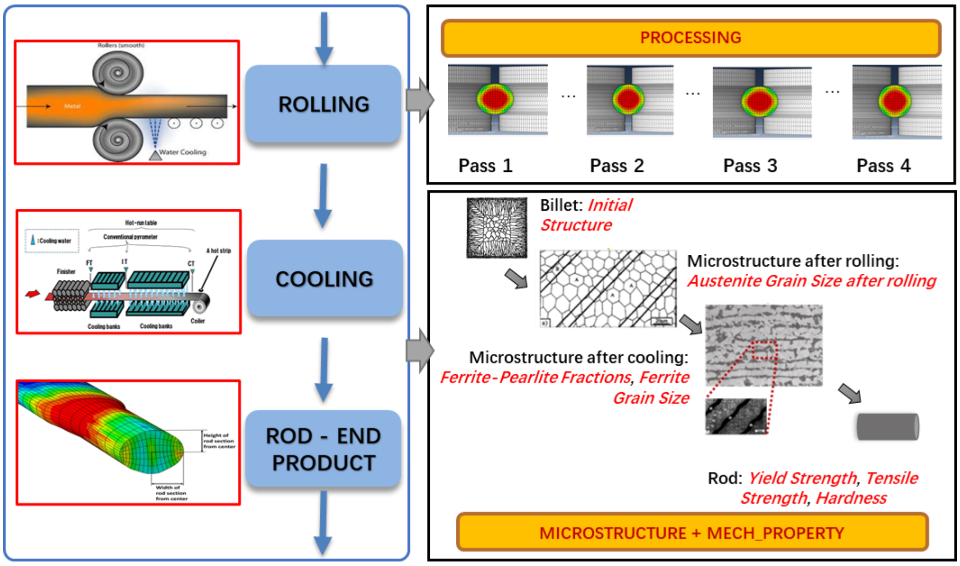

Figure 10. Co-design of materials, products, and manufacturing processes in the HRRS

- ***Management of system complexity***

The manufacturing process information flows in the HRRS design involve individual processes happening at different levels for each unit operation and the information flows cover the design objectives and models of various fields, taking into account material behaviors at multiple scales. Based on the complexity management and design guidance procedure defined in Section 4, the top-level design users of the KBDGS for the HRRS design (e.g., the roles of system managers) can identify the multi-domain system concepts for the design scenarios of a specific stage, and preliminarily determine design attributes of the system concept to meet the overall system design requirements. Figure 11 displays one of these possible design scenarios, for which we assume that the designers are primarily concerned with the rolling module and the cooling module. Thus, system concepts C_1 and C_2 that correspond to the HRRS design are identified. For system concept C_1, the designer focuses on the overall system performance of the HRRS, including the system load, throughput, and ovality of the rod. For system concept C_2, the mechanical performances and material properties of the product are the design points. As mentioned in Section 4.1, the system concepts' design attributes are clarified to enable designers to address system complexity by refining a given system concept. In addition to the system performance in the rolling module (C_1), the material designers pay more attention to material properties in the thermo-mechanical processing design problem (C_3). The system concept C_2 highlights the problem model used to solve the decision with and without uncertainty. Thus, different stakeholders in the complex engineered systems design can gradually create and visualize design problems for various design scenarios by representing a system concept network, which provides a concise and effective way to manage system complexity.

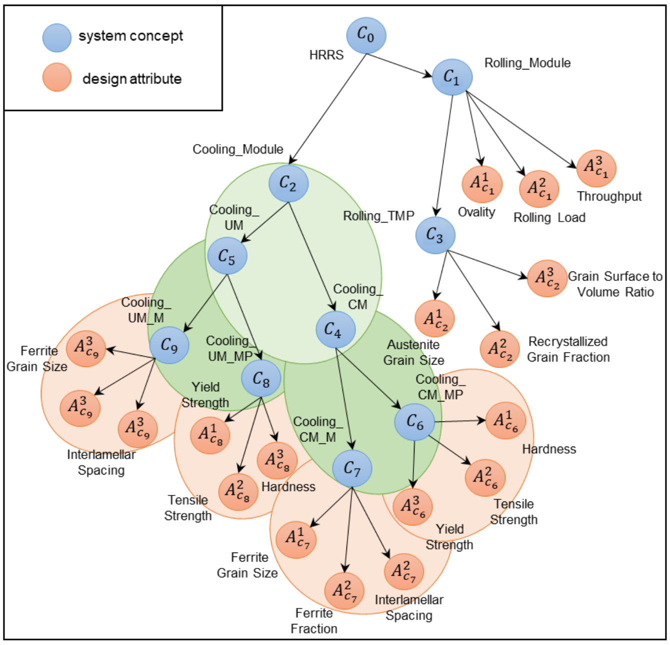

Figure 11. The network of the system concept and its design attributes for the HRRS design

- ***Management of process complexity***

In addition to the visualization of design problems representing system concept networks, the more important function of the KBDGS is to manage the decision process complexity with the PEI-X diagram, which supports establishing decision-centric problem-solving processes for the node in the system concept networks. As shown in Figure 12, designers can carry out the solution of a specific concept by establishing a hierarchical decision workflow. A sequential four-pass rolling model is formulated corresponding to four rolling passes. The forward model chain is formed to solve the system concept C_1 (as shown in ① in Figure 12) and to identify the set points of each rolling pass involved. To determine the identified design attributes, an inverse design information flow is generated in the decision workflow from the event node of Pass 4 to Pass 1. As for the system concept C_2 defined in the cooling module, the design scenarios that are defined emphasize the system model with and without uncertainty (as shown ② in Figure 12). Different design scenarios correspond to different design phase processes, in which each phase node is further refined into a decision workflow composed of different design events, such as $P_{C_2}^1$ being partitioned into $E_{P_1}^1$ (design product mechanical performance) and $E_{P_1}^2$(design microstructure material properties). A specific event process node can be partitioned into different activities of tasks and decisions, including the identification of system goals, variables, bounds, and other elements in the decision space, as well as the instantiation of mathematical functions, decision-solving, and post-solution analysis. For example, $E_{P_1}^1$ is partitioned into $T_{E_1}^1$, $T_{E_1}^2$, $T_{E_1}^3$, and $D_{E_1}^1$. The reusability information and knowledge involved in each task and decision can be further represented and established using more granular knowledge icons, as defined in Section 4.3 (as shown Figure 7). It can be found that the icon-based process modeling method can be more flexible for representing decision-making processes with different design strategies. The process nodes with different granularities can effectively capture the reusable information in the decision-making and manage the generation, utilization, and iteration of design information at different design levels in the way of the workflow. More importantly, the icons used to represent the relevant information for specific decisions in the framework proposed in this paper are extensible and scalable. For example, more specific icons can be developed to enrich the existing *Task* icon, *Knowledge* icon, and *Information* icon.

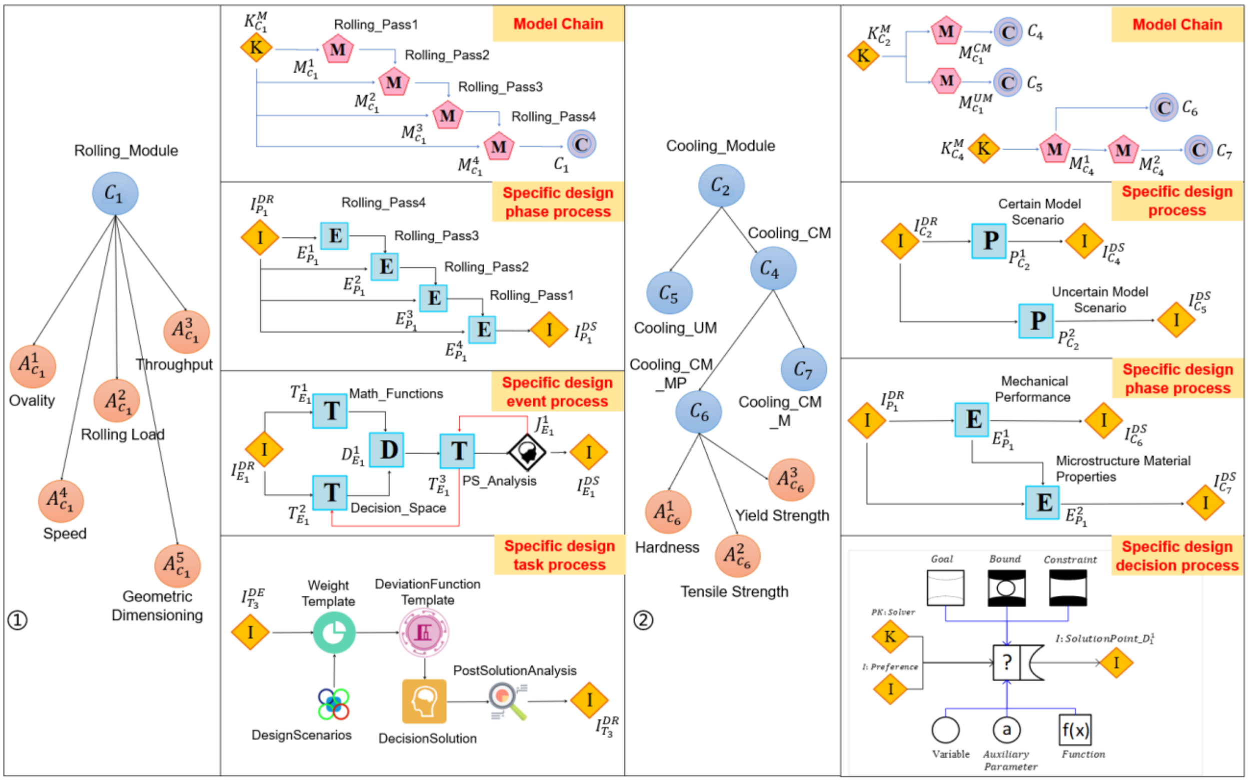

Figure 12. Decision workflows involved in the HRRS design

- ***Management of design complexity***

To facilitate designers making the utmost of decision workflows established with the PEI-X diagram to reasonably solve design problems, the decision guidance procedure (i.e., FREI) defined in Section 4.4 is implemented to manage the complexity of the decision-centric design. This is an interactive decision-making process. That is, designers need to explore and iterate until they find a satisfying solution according to the design results determined by an initial design space and then complete the refinement and improvement of the decision process for a given system concept. As shown in Figure 13, the event process node $E_{P_1}^1$ is created to address the design problem of "Rolling Pass 4" for system concept C_1. Based on the decision workflow established in Figure 12, relevant activity information for *Task* and *Decision* is captured by the event node properties (see [12] for more detailed node properties). Here, we emphasize the design exploration tasks and the reusability of their process templates. In the task instance $T^3_{E_1}$, nineteen different scenarios with different weights for the goal in Pass 4 are exercised [56]. Different design scenarios focus on exploring different decision-making preferences [59], such as achieving one of the goals' targets, having an equal preference for each goal, and giving greater preference to some of the goals. As a result, goal solution spaces for different design scenarios are obtained and presented visually to help the designer define each goal's achievement and determine a common region that meets all design requirements. Template-based process reuse in the KBDGS can help designers improve this iterative process and thus enhance decision efficiency [59]. In the HRRS case, the designer can reuse the post-solution analysis task process established in Figure 12 to obtain the solution space for different concepts, viz., $E^1_{P_1}$ for C_1 and $E^1_{P_1}$ for C_4. The detailed solution space exploration of those two concepts is illustrated in [12], and we also define the systematic design space exploration in [59], including sensitivity analysis and design space adjustment. Thus, in terms of complex engineered systems design, the proposed method and tool based on the KBDGS can effectively facilitate design complexity management, especially design exploration.

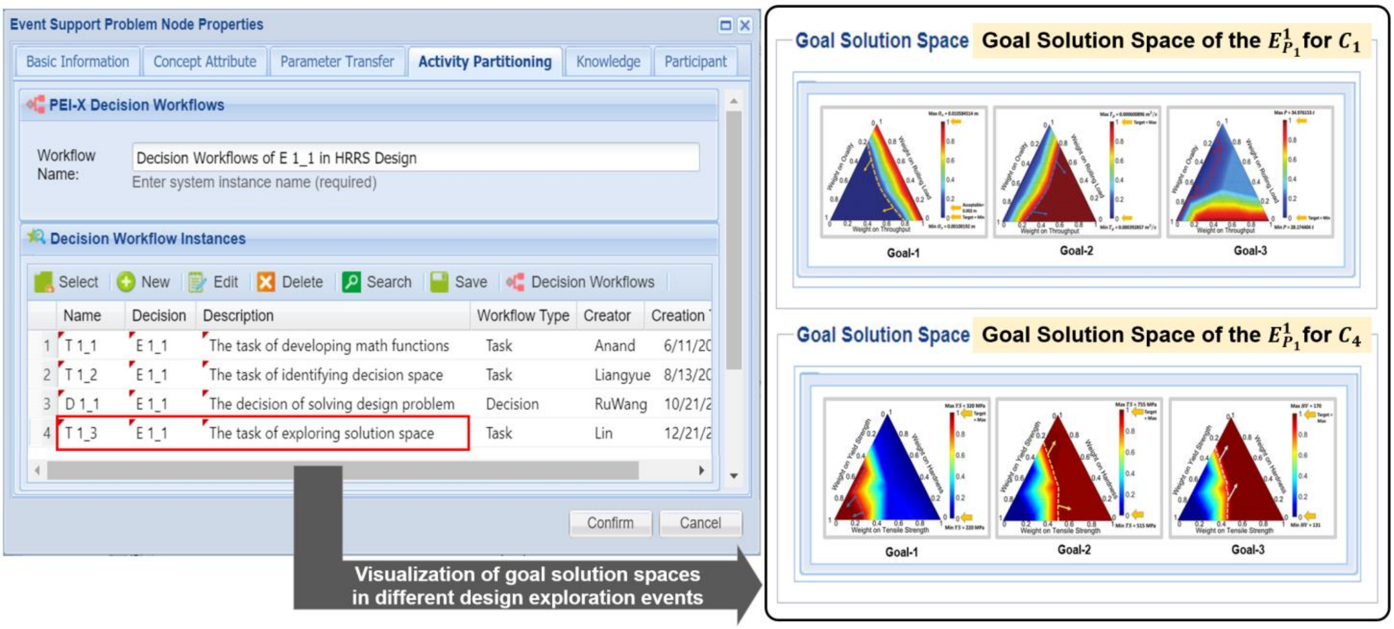

Figure 13. Event process node property interface and solution spaces for design exploration

- ***Management of organizational complexity***

In the KBDGS, organizational complexity management is reflected in the definition of different decision-maker roles in the system setting, as detailed in Section 4,1. As shown in Figure 9, different role users enter their respective workspace and configure their functional responsibilities via role permission setting. Moreover, the web-based access mode adopted in the KBDGS can achieve distributed management and collaborative decision-making in complex engineered systems design. In particular, three role assumptions we have given, for roles with different domain backgrounds, are also involved in HRRS design, such as materials, the manufacturing process, and mechanical engineering. The role allocation of decision-making stakeholders helps increase the iteration in the design and execution of decision processes (the participant panel in each process node property, as seen in Figure 12), thus ensuring the integrated realization of the system, process, and design complexity.

5.2. Uncertainty Management Case in the KBDGS: Networked Manufacturing Systems Design

Networked manufacturing systems (NMSs) are complex processes consisting of one or more operations to assemble or manufacture a product. Usually, this requires one or more interconnected manufacturing stations. Typical examples of NMSs are automotive machining and assembly lines, electronic assembly and packaging processes, and semiconductor lithography processes [83]. NMSs are continuous processes for which different manufacturing operations are performed at each stage. In assembly lines, a major cause of dimensional variation in the product is the imprecise fixture of parts and/or the deterioration of tools and sensors over time. Such errors (dimensional variations in quality) being introduced at any station can propagate through the remainder of the process (as illustrated in ① of Figure 14) and affect the final product quality. The inability to accurately detect the position and orientation of parts and perform operations within specified tolerances can lead to an excessive variation in the final product's dimensional quality. This resulting degradation of quality negatively impacts productivity and efficiency, increasing the process cost [83]. In designing a flexible, adaptable manufacturing process, an

NMSs designer faces two main challenges: system complexity and managing uncertainty. In terms of complexity, frequent challenges include obtaining systematic solutions to highly complex design problems, managing multiple sources of variability that are impossible to remove, and managing variability in the process that increases cost and jeopardizes quality. In terms of uncertainty, frequent challenges include managing uncertainty in the simulation process parameters such as sensor noise and disturbances, managing uncertainty in the model parameters such as deviations in the position of tools and sensors, managing model structure uncertainty such as simplifications and assumptions that the designer makes due to a lack of domain knowledge or a lack of data, and managing uncertainty due to propagated uncertainty in the chain of models [82].

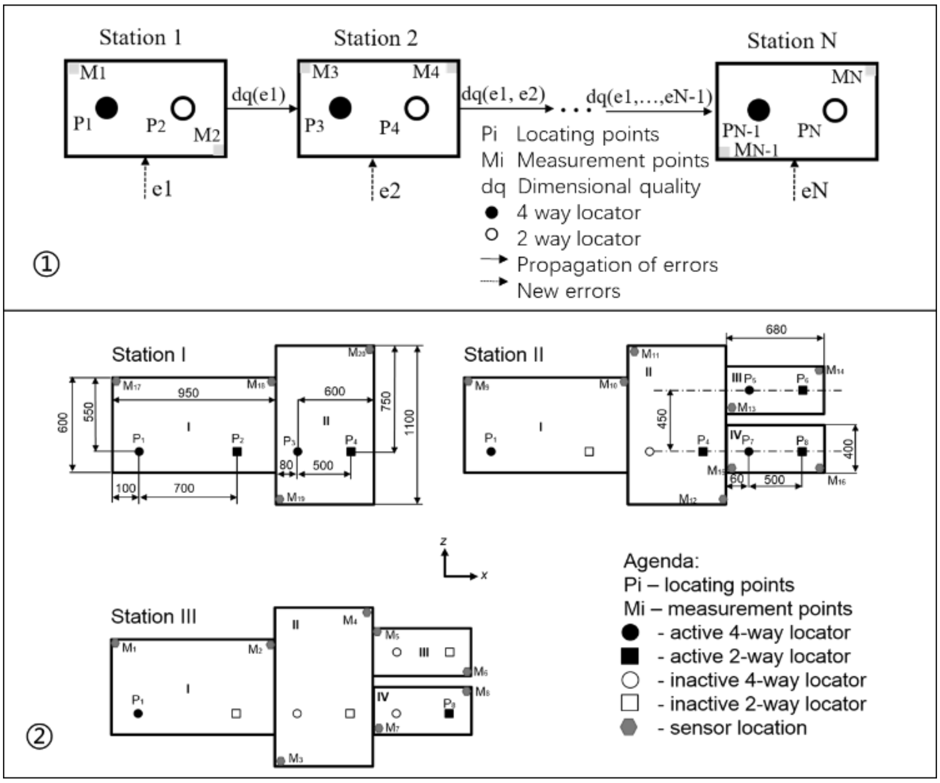

Figure 14. Error introduction and propagation in NMSs [83]

- ***Management of problem modeling with uncertainty***

In terms of problem modeling, the challenge of detecting and correcting dimensional variations can be addressed by the selection of appropriate sensors at the design time. The selection and placement of the sensors will ensure that the overall Multi-stage Manufacturing Process (MMP) is diagnosable, i.e., that the variations in product dimensions can be detected and their cause can be isolated. However, several choices for the sensors and their placements are necessary to address these choices' impact at the design time. For example, the design problem is exemplified through a two-dimensional (as shown in ② in Figure 14) automotive panel stamping process in which four parts are assembled across three stations [84, 85]. The procedure of design guidance for decision support is shown in Figure 15.

(1) *Designing NMSs concurrently*: The initial design parameters and assumptions are set, such as the number of operational stations, the number of parts to be assembled, the use of programmable tooling control actions, and 2-D rigid body parts, as shown in ① in Figure 15. The flexible design parameters are identified, such as attributes of a tool, e.g., type (here the 4-way or 2-way fixture locator in Figure 15), number (Pi in ② of Figure 15), and its location in the process, and the attributes of a sensor, e.g., type, number of sensors (Mi in ② of Figure 15), and the location of the sensor in the process. The connectivity of the design parameters is established, and the process is represented by a comprehensive state-space model (SoV), as shown in ② in Figure 15.

(2) *Managing problem structure*: The comprehensive SoV model has high dimensionality, high complexity, and it is computationally expensive to solve. Hence, it is partitioned into sub models: process decision models (observability, diagnosability, controllability, and cost, as shown in ③ in Figure 15) and performance observation models (quality, as shown in ③ in Figure 15) formulated as compromise decision support problems (cDSPs). The cDSPs are interconnected, and the feasible design space is identified, as shown in ④ in Figure 15.

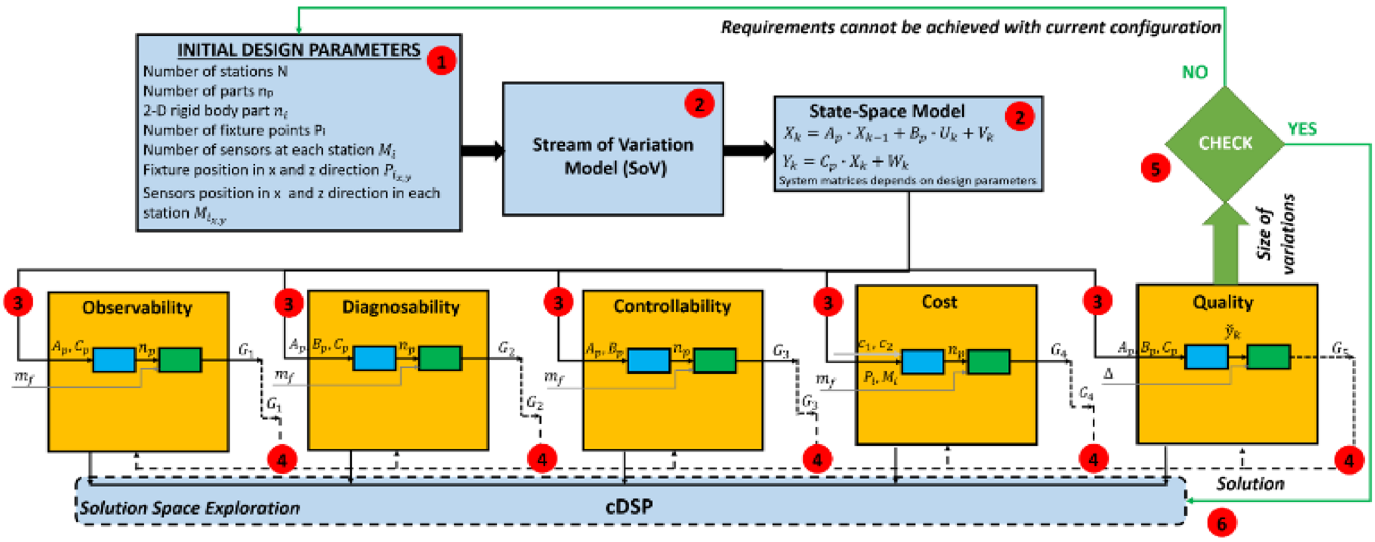

Figure 15. Adaptable design of Networked Manufacturing Systems [83]

In the modeling of the problem, designers have to clarify the information flow relationship for different design scenarios before establishing the decision network for the NMSs design. Utilizing the PEI-X diagram provided in the KBDGS, the problem model structure used to describe the logical relationship between a large number of parameters in NMSs design is constructed, as shown in Figure 16. The combined model (CM) is used to integrate individual problem modes for diagnosability (D), controllability (C), and cost-effectiveness (E), and then the CM is interconnected with the performance measurement model (PM) used to observe product quality. Here, four types of uncertainty are integrated and managed to attain robust design.

(1) *Uncertainty Type I in Performance Measurement Model* (M_{PM_U1}) - unpredictability of a mechanical system in MMP (i.e., simulation process parameters that are uncontrollable system parameters), such as sensor noise due to random false measurements sent by sensors and process disturbances due to random changes in the process (temperature, pressure in the working environment, etc.).

(2) *Uncertainty Type II in Performance Measurement Model* (M_{PM_U2}) - unpredictability in model parameters due to incomplete knowledge of model parameters and inputs such as tooling parameters or fixture points in the multistage assembling process and sensing parameters (sensors) in the process.

(3) *Uncertainty Type III in Combined Model* (M_{CM_U3}) - model structure unpredictability in MMP due to uncertain model formulation and simplification in a model, such as model simplifications that are made in the controllability model where the sensors and sensing stations of a physical system in MMP are controllable system variables that control the process performance.

(4) *Uncertainty Type IV in Combined Model* (M_{CM_U4}) - propagated uncertainty as a combination of forward- mentioned uncertainty in the model chain of MMP, such as different combinations of D, C, and E in the CM.

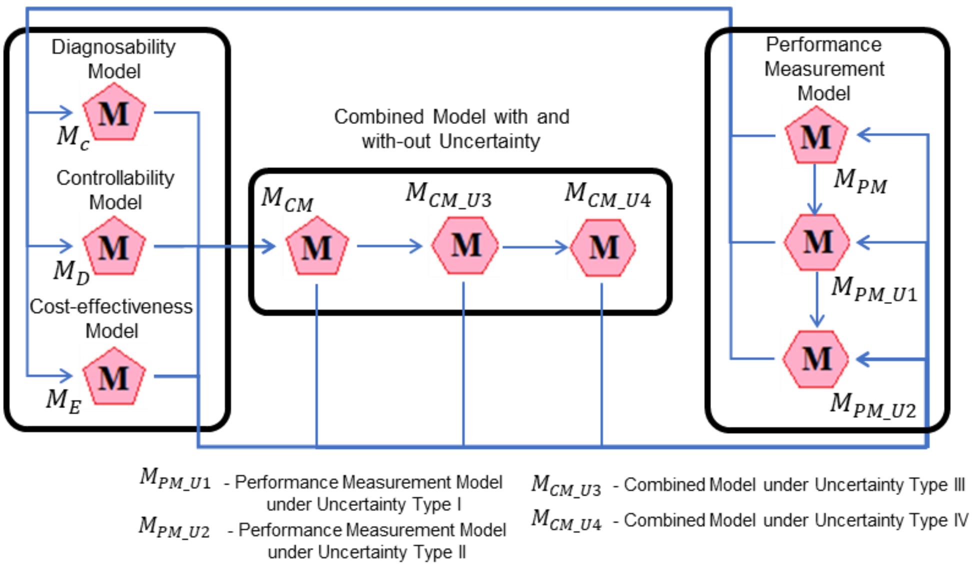

Figure 16. Problem model structure of the NMSs design with and without uncertainty

- ***Management of decision process with uncertainty***

According to the model chain identified in Figure 16, decision workflows are formulated to identify a possible solution for the design criteria and its effect on the overall cost, as shown in Figure 17. Here, different design scenarios for the same problem model are considered, including different model inputs, model structure, and models with uncertainty. For example, the design scenarios DS_D and DS_C are defined to minimize the total number of sensors and sensing stations related to diagnosability/controllability, then the changes of the process diagnosability and controllability with the change of the total number of sensors and sensing stations are found for all sensor distribution schemes. In terms of the performance model (PM), three decision models (*decision process nodes*) are established to analyze the solution spaces of the combined model while minimizing the expected variations in the process. To determine the minimal number of sensors and sensing stations in the process and the most adequate sensor distribution schemes with and without uncertainty, the decision problems of the combined model (state-space models) focus on the design space exploration of the comprehensive mathematical model involved in the problem-solving of the diagnosability model, controllability model, and cost-effectiveness model. It can be seen that the KBDGS can effectively manage the model information interaction in the adaptive design of NMSs with uncertainty.

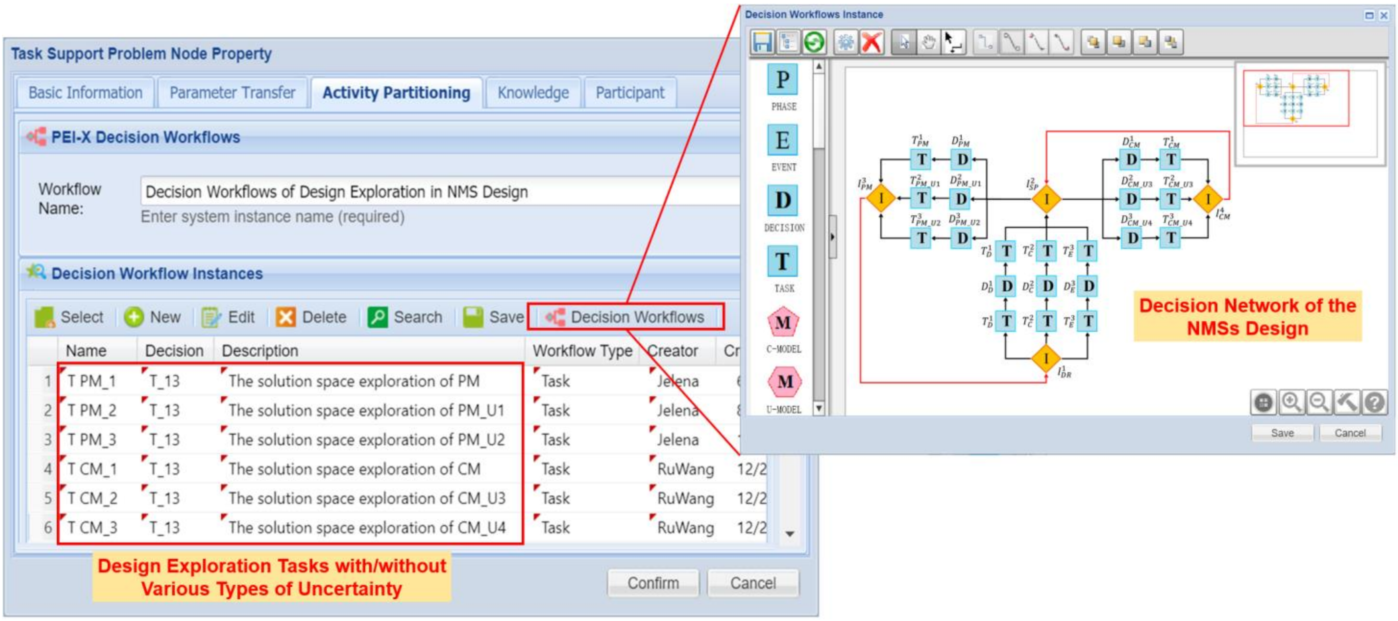

Figure 17. Design exploration tasks related to the decision network of NMSs design

- ***Management of design exploration with uncertainty***

The NMSs are not inherently diagnosable and controllable, but rather they need to be designed to be so. Often, there is more than one way of accomplishing this, especially if the system's model is unknown or inaccurate, in which case the solution space will change. Furthermore, if there is uncertainty in the process, it is difficult to identify the right solution. In the NMSs design, as shown in 2 in Figure 14, the problem is to determine tooling and sensing arguments to design a system that is cost-effective, diagnosable, and controllable, and that has a solution that is robust even in the presence of uncertainty. As a result, the designer executes the decision workflows established in Figure 17 in KBDGS, specifically, the design exploration tasks for the PM and CM problem models (i.e., $T_{PM}^1, T_{PM\_U1}^2, T_{PM\_U2}^3, T_{CM}^1, T_{CM\_U3}^2, T_{CM\_U4}^3$). Similarly, with the utilization of the KBDGS provided by the goal solution space visualization (as shown in Figure 18), the designer can identify the number of sensors and sensing stations that give a satisfactory dimensional quality, and the cost is determined. The red regions in Figure 18 give favorable results, while the blue and purple regions give less favorable results. More details of the uncertainty management of NMSs design are given in [62]. It can be seen that the KBDGS can effectively manage solution space exploration for different scenarios and identify whether the formulations of the decision models (D, C, E) or the combined model (CM) are adequate and produce robust solutions, or whether there is a need to adjust any of the models.

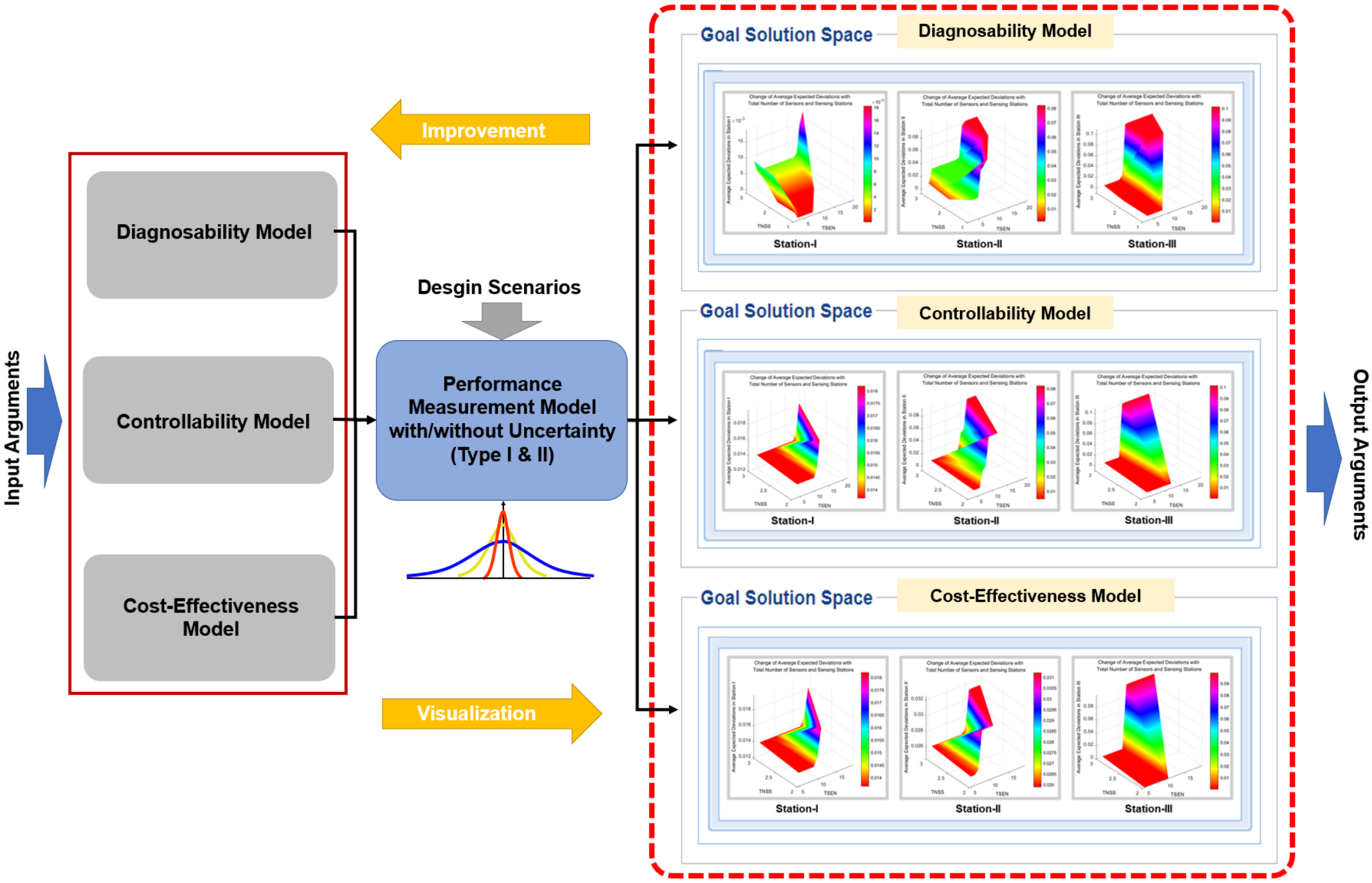

Figure 18. Solution space exploration management of NMSs design with uncertainty

5.3. Discussion and Limitations

Industry 4.0 varies for the different domain decision problems addressed in complex engineered systems design. Our focus is to identify the functional demands of decision support in the digital design paradigm and provide design guidance with more flexibility and adaptability. To validate this purpose, the proposed KBDGS architecture is applied in the design of HRRS and NMSs, and special emphasis is placed on the effective management of complexity and uncertainty. As shown in Figure 19, compared with the existing methods (reviewed in Section 2.1 and 2.2), the filling of research gaps (defined in Section 2.3) is embodied in the following aspects of contributions:

(1) Illustrating the verification of the decision functional demands identified in Section 3 and the corresponding functional framework of the KBDGS identified in Section 4. As significant contributions of this paper, identifying the demands and functional characteristics is the premise and foundation for the KBDGS to realize the value of decision support in complex engineered systems design. The HRRS and NMSs design cases are illustrated based on the four aspects of system, process, design, and organization involved in complexity management, as well as the problem modeling, decision process, and robust design exploration involved in uncertainty management. Knowledge management focuses more on domain knowledge related to the two design cases, which is not the focus of this paper. The efficacy of the related work involved in knowledge management (i.e., categorization, modeling, capture, and reuse) has been verified in previous studies [12, 13, 59, 70].

(2) Illustrating the KBDGS's efficiency and effectiveness for the decision support. The two design cases are detailed in [56, 62] with respect to complexity, uncertainty, and knowledge. The point here is to implement integrated management via the CDK closed-loop framework and systematic design guidance (i.e., the FREI method) defined in Section 4. The icon-based knowledge templates and decision workflows (i.e., the PEI-X diagram) can increase the efficiency of information interaction and design iteration. The graphics and the visualization can also enhance the insight of decision-makers. However, the proposed architecture needs to be further improved to ensure the universality of complex engineered systems design problems, especially in the dynamic management of decision networks. Industrial applications closer to the digital scenarios need to be validated and the measured impacts of the KBDGS need to be defined in terms of the complexity, uncertainty, and knowledge management.

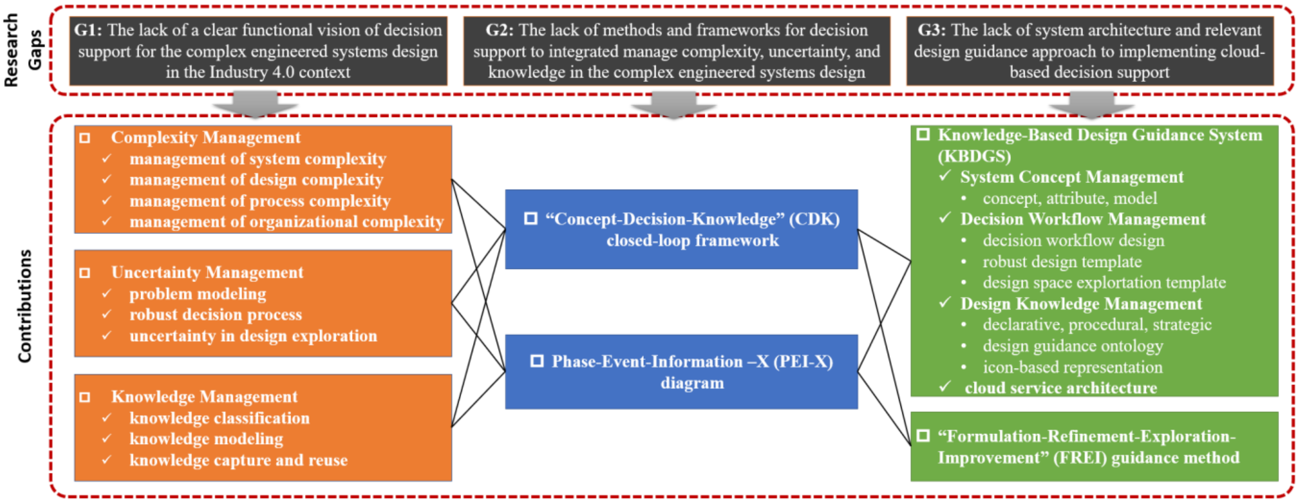

Figure 19. Mapping between research gaps and the KBDGS's contributions

6. Closure

As the fourth industrial revolution, Industry 4.0 is bringing about digital transformations regarding all aspects of product realization and the challenges arising in the integration of cyber-systems and physical resources. The impact of these transformations exceeds the production systems themselves; rather, they affect the entire value chain, from the product design through the manufacturing to supply-chain management and product service, even social service. In this paper, design problems in different stages of product value chain realization are collectively referred to as the value-chain centric complex engineered systems design lifecycle, which involves the decision-making characteristics of five specific domains typical in the Industry 4.0 era: physics, production, cyber, society, and service. The automation and intelligence highlighted in Industry 4.0, characterized by the convergence of different technologies, puts forward higher requirements for a reasonable trade-off between humans and machines for decision-making governance. However, in the context of Industry 4.0, the vision of decision support for design engineering is still unclear. In addition, the corresponding methods and system architecture are also lacking to support the realization of industrial applications.

By investigating the design approaches of typical complex engineered systems represented by CPS, PSS, CPPS, and CPPSS, as well as decision support characteristics in the Industry 4.0 era, we present decision support demands based on the aspects of complexity, uncertainty, and knowledge. As a response, the architecture of a Knowledge-Based Design Guidance System (KBDGS) for cloud-based decision support is proposed. This architecture highlights the integrated management of complexity, uncertainty, and knowledge in designing decision workflows leveraging the PEI-X diagram, as well as systematic design guidance to find satisfying solutions with the iterative process of the concept-decision-knowledge (CDK) closed-loop, namely "Formulation-Refinement-Exploration-Improvement" (FREI). Finally, we apply the KBDGS developed in this paper to solve two design cases, namely Hot Rod Rolling System (HRRS) and Networked Manufacturing Systems (NMSs), and we demonstrate the KBDGS's efficacy in the management of complexity and uncertainty. The contribution of this paper provides design guidance to facilitate knowledge discovery, capture, and reuse in the context of decision-centric digital design, thus improving the efficiency and effectiveness of decision-making in complex engineered systems design, as well as the evolution of decision support in the field of design engineering in the age of the Industry 4.0 innovation paradigm.

The emphasis of future work will be placed on the adaptability and intelligence of the KBDGS. That is, enriching icons with more functions in the PEI-X diagram and strengthening the intellectualization of design guidance in managing complexity and uncertainty to improve decision-making efficiency.

Acknowledgment

Ru Wang gratefully acknowledges the Project funded by China Postdoctoral Science Foundation (Grant 2018M640073). Guoxin Wang gratefully acknowledges the National Ministries Projects of China (Grant JCKY2017207A001). This paper is an outcome of the International Systems Realization Partnership between the Institute for Industrial Engineering @ The Beijing Institute of Technology, China, The Systems Realization Laboratory @ The University of Oklahoma, the USA, and The Systems Realization Laboratory @ The University of Liverpool, the UK.

References

[1] Esmaeilian, B., Behdad, S., and Wang, B., 2016, "The evolution and future of manufacturing: A review," Journal of Manufacturing Systems, 39, pp. 79-100.

[2] Oztemel, E., and Gursev, S., 2020, "Literature review of Industry 4.0 and related technologies," Journal of Intelligent Manufacturing, 31(1), pp. 127-182.
[3] Zheng, P., wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., Yu, S., and Xu, X., 2018, "Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives," Frontiers of Mechanical Engineering, 13(2), pp. 137-150.
[4] Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., Son, J. Y., Kim, B. H., and Noh, S. D., 2016, "Smart manufacturing: Past research, present findings, and future directions," International Journal of Precision Engineering and Manufacturing-Green Technology, 3(1), pp. 111-128.
[5] Lim, K. Y. H., Zheng, P., and Chen, C.-H., 2020, "A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives," Journal of Intelligent Manufacturing, 31(6), pp. 1313-1337.
[6] Milisavljevic-Syed, J., Thames, J.L., and Schaefer, D., 2019, "The Digitization of Design and Manufacturing: A State-of-the-Art Report on the Transition from Strategic Vision to Implementation in Industry," Procedia CIRP.
[7] Wang, K., Jiang, Z., Peng, B., and Jing, H., 2020, "Servitization of manufacturing in the new ICTs era: A survey on operations management," Frontiers of Engineering Management.
[8] Hoffmann Souza, M. L., da Costa, C. A., de Oliveira Ramos, G., and da Rosa Righi, R., 2020, "A survey on decision-making based on system reliability in the context of Industry 4.0," Journal of Manufacturing Systems, 56, pp. 133-156.
[9] Wiesner, S., and Thoben, K.-D., 2017, "Cyber-physical product-service systems," Multi-disciplinary engineering for cyber-physical production systems, Springer, pp. 63-88.
[10] Zhong, R. Y., Xu, X., Klotz, E., and Newman, S. T., 2017, "Intelligent Manufacturing in the Context of Industry 4.0: A Review," Engineering, 3(5), pp. 616-630.
[11] Li, Q., Tang, Q., Chan, I., Wei, H., Pu, Y., Jiang, H., Li, J., and Zhou, J., 2018, "Smart manufacturing standardization: Architectures, reference models and standards framework," Computers in Industry, 101, pp. 91-106.
[12] Wang, R., Nellippallil, A. B., Wang, G., Yan, Y., Allen, J. K., and Mistree, F., 2020, "A Process Knowledge Representation Approach for Decision Support in Design of Complex Engineered Systems," Advanced Engineering Informatics.
[13] Wang, R., Wang, G., Yan, Y., Sabeghi, M., Ming, Z., Allen, J. K., and Mistree, F., 2019, "Ontology-based representation of meta-design in designing decision workflows," Journal of Computing and Information Science in Engineering, 19(1), p. 011003.
[14] Mourtzis, D., Fotia, S., Boli, N., and Pittaro, P., 2018, "Product-service system (PSS) complexity metrics within mass customization and Industry 4.0 environment," The International Journal of Advanced Manufacturing Technology, 97(1), pp. 91-103.
[15] Leitão, P., Colombo, A. W., and Karnouskos, S., 2016, "Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges," Computers in Industry, 81, pp. 11-25.
[16] Biffl, S., Lüder, A., and Gerhard, D., 2017, Multi-Disciplinary Engineering for Cyber-Physical Production Systems, Springer International Publishing.
[17] Frazzon, E. M., Agostino, Í. R. S., Broda, E., and Freitag, M., 2020, "Manufacturing networks in the era of digital production and operations: A socio-cyber-physical perspective," Annual Reviews in Control, 49, pp. 288-294.
[18] Moghaddam, M., Cadavid, M. N., Kenley, C. R., and Deshmukh, A. V., 2018, "Reference architectures for smart manufacturing: A critical review," Journal of Manufacturing Systems, 49, pp. 215-225.
[19] Park, K. T., Lee, J., Kim, H.-J., and Noh, S. D., 2020, "Digital twin-based cyber physical production system architectural framework for personalized production," The International Journal of Advanced Manufacturing Technology, 106(5), pp. 1787-1810.
[20] Ribeiro, L., and Hochwallner, M., 2018, "On the Design Complexity of Cyberphysical Production Systems," Complexity.
[21] Francalanza, E., Borg, J., and Constantinescu, C., 2017, "A knowledge-based tool for designing cyber physical production systems," Computers in Industry, 84, pp. 39-58.

[22] Zeng, J., Yang, L. T., Lin, M., Ning, H., and Ma, J., 2020, "A survey: Cyber-physical-social systems and their system-level design methodology," Future Generation Computer Systems, 105, pp. 1028-1042.
[23] Dantan, J.-Y., El Mouayni, I., Sadeghi, L., Siadat, A., and Etienne, A., 2019, "Human factors integration in manufacturing systems design using function–behavior–structure framework and behaviour simulations," CIRP Annals, 68(1), pp. 125-128.
[24] Sgarbossa, F., Grosse, E. H., Neumann, W. P., Battini, D., and Glock, C. H., 2020, "Human factors in production and logistics systems of the future," Annual Reviews in Control, 49, pp. 295-305.
[25] Qu, M., Yu, S., Chen, D., Chu, J., and Tian, B., 2016, "State-of-the-art of design, evaluation, and operation methodologies in product service systems," Computers in Industry, 77, pp. 1-14.
[26] Vasantha, G. V. A., Roy, R., Lelah, A., and Brissaud, D., 2012, "A review of product–service systems design methodologies," Journal of Engineering Design, 23(9), pp. 635-659.
[27] Bertoni, A., Bertoni, M., Panarotto, M., Johansson, C., and Larsson, T. C., 2016, "Value-driven product service systems development: Methods and industrial applications," CIRP Journal of Manufacturing Science and Technology, 15, pp. 42-55.
[28] Lee, C.-H., Chen, C.-H., Li, F., and Shie, A.-J., 2020, "Customized and knowledge-centric service design model integrating case-based reasoning and TRIZ," Expert Systems with Applications, 143, p. 113062.
[29] Waris, M. M., Sanin, C., and Szczerbicki, E., 2018, "Smart Innovation Engineering: Toward Intelligent Industries of the Future," Cybernetics and Systems, 49(5-6), pp. 339-354.
[30] Lee, C.-H., Chen, C.-H., and Lee, Y.-C., 2020, "Customer requirement-driven design method and computer-aided design system for supporting service innovation conceptualization handling," Advanced Engineering Informatics, 45, p. 101117.
[31] Benabdellah, A. C., Bouhaddou, I., Benghabrit, A., and Benghabrit, O., 2019, "A systematic review of design for X techniques from 1980 to 2018: concepts, applications, and perspectives," The International Journal of Advanced Manufacturing Technology, 102(9), pp. 3473-3502.
[32] Li, X., Chen, C.-H., Zheng, P., Wang, Z., Jiang, Z., and Jiang, Z., 2020, "A Knowledge Graph-Aided Concept–Knowledge Approach for Evolutionary Smart Product–Service System Development," Journal of Mechanical Design, 142(10).
[33] Yang, L., Cormican, K., and Yu, M., 2019, "Ontology-based systems engineering: A state-of-the-art review," Computers in Industry, 111, pp. 148-171.
[34] Thomsen, B., Kokkolaras, M., Mansson, T., and Isaksson, O., 2017, "Quantitative Assessment of the Impact of Alternative Manufacturing Methods on Aeroengine Component Lifing Decisions," Journal of Mechanical Design, 139(2).
[35] Mourtzis, D., Papatheodorou, A. M., and Fotia, S., 2018, "Development of a Key Performance Indicator Assessment Methodology and Software Tool for Product- Service System Evaluation and Decision-Making Support," Journal of Computing and Information Science in Engineering, 18(4).
[36] Sakao, T., and Lindahl, M., 2012, "A value based evaluation method for Product/Service System using design information," CIRP Annals, 61(1), pp. 51-54.
[37] Rondini, A., Bertoni, M., and Pezzotta, G., 2020, "At the origins of Product Service Systems: Supporting the concept assessment with the Engineering Value Assessment method," CIRP Journal of Manufacturing Science and Technology, 29, pp. 157-175.
[38] Costa, N., Patrício, L., Morelli, N., and Magee, C. L., 2018, "Bringing Service Design to manufacturing companies: Integrating PSS and Service Design approaches," Design Studies, 55, pp. 112-145.
[39] Garetti, M., Rosa, P., and Terzi, S., 2012, "Life Cycle Simulation for the design of Product–Service Systems," Computers in Industry, 63(4), pp. 361-369.
[40] Bertoni, A., and Bertoni, M., 2020, "PSS cost engineering: A model-based approach for concept design," CIRP Journal of Manufacturing Science and Technology, 29, pp. 176-190.
[41] Andriankaja, H., Boucher, X., and Medini, K., 2018, "A method to design integrated product-service systems based on the extended functional analysis approach," CIRP Journal of Manufacturing Science and Technology, 21, pp. 120-139.
[42] Pereira Pessôa, M. V., and Jauregui Becker, J. M., 2020, "Smart design engineering: a literature review of the impact of the 4th industrial revolution on product design and development," Research in Engineering Design, 31(2), pp. 175-195.

[43] Burggräf, P., Wagner, J., and Weißer, T., 2020, "Knowledge-based problem solving in physical product development—A methodological review," Expert Systems with Applications, 5, p. 100025.
[44] Umeda, Y., Takata, S., Kimura, F., Tomiyama, T., Sutherland, J. W., Kara, S., Herrmann, C., and Duflou, J. R., 2012, "Toward integrated product and process life cycle planning—An environmental perspective," CIRP Annals, 61(2), pp. 681-702.
[45] Xu, Y., Bernard, A., Perry, N., Xu, J., and Sugimoto, S., 2014, "Knowledge evaluation in product lifecycle design and support," Knowledge-Based Systems, 70, pp. 256-267.
[46] Agostinho, C., Ducq, Y., Zacharewicz, G., Sarraipa, J., Lampathaki, F., Poler, R., and Jardim-Goncalves, R., 2016, "Towards a sustainable interoperability in networked enterprise information systems: Trends of knowledge and model-driven technology," Computers in Industry, 79, pp. 64-76.
[47] Duan, Y., Edwards, J. S., and Dwivedi, Y. K., 2019, "Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda," International Journal of Information Management, 48, pp. 63-71.
[48] Kheybari, S., Rezaie, F. M., and Farazmand, H., 2020, "Analytic network process: An overview of applications," Applied Mathematics and Computation, 367, p. 124780.
[49] Ding, R.-X., Palomares, I., Wang, X., Yang, G.-R., Liu, B., Dong, Y., Herrera-Viedma, E., and Herrera, F., 2020, "Large-Scale decision-making: Characterization, taxonomy, challenges and future directions from an Artificial Intelligence and applications perspective," Information Fusion, 59, pp. 84-102.
[50] Soman, D., and Nmarandi, S., 2015, "Managing Customer Value," American Journal of Business, 14(1), pp. 13-22.
[51] Terziyan, V., Gryshko, S., and Golovianko, M., 2018, "Patented intelligence: Cloning human decision models for Industry 4.0," Journal of Manufacturing Systems, 48, pp. 204-217.
[52] Bendul, J. C., and Blunck, H., 2019, "The design space of production planning and control for industry 4.0," Computers in Industry, 105, pp. 260-272.
[53] Theorin, A., Bengtsson, K., Provost, J., Lieder, M., Johnsson, C., Lundholm, T., and Lennartson, B., 2017, "An event-driven manufacturing information system architecture for Industry 4.0," International Journal of Production Research, 55(5), pp. 1297-1311.
[54] Shahin, M., Chen, F. F., Bouzary, H., and Krishnaiyer, K., 2020, "Integration of Lean practices and Industry 4.0 technologies: smart manufacturing for next-generation enterprises," The International Journal of Advanced Manufacturing Technology, 107(5), pp. 2927-2936.
[55] Babiceanu, R. F., and Seker, R., 2016, "Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook," Computers in Industry, 81, pp. 128-137.
[56] Nellippallil, A. B., Allen, J., Gautham, B., Singh, A., and Mistree, F., 2020, Architecting Robust Co-Design of Materials, Products, and Manufacturing Processes.
[57] Milisavljevic-Syed, J., Allen, J. K., Commuri, S., and Mistree, F., 2019, "Design of networked manufacturing systems for Industry 4.0," Procedia CIRP, 81, pp. 1016-1021.
[58] Cardin, M.-A., 2014, "Enabling Flexibility in Engineering Systems: A Taxonomy of Procedures and a Design Framework," Journal of Mechanical Design, 136.
[59] Wang, R., Nellippallil, A. B., Wang, G., Yan, Y., Allen, J. K., and Mistree, F., 2018, "Systematic design space exploration using a template-based ontological method," Advanced Engineering Informatics, 36, pp. 163-177.
[60] Benabdellah, A. C., Benghabrit, A., and Bouhaddou, I., 2020, "Complexity drivers in engineering design Toward a decision support system based on an organizational perspective," Journal of Engineering Design and Technology.
[61] Smith, W. F., Milisavljevic, J., Sabeghi, M., Allen, J. K., and Mistree, F., "The Realization of Engineered Systems with Considerations of Complexity," Proc. ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, American Society of Mechanical Engineers, pp. V007T006A019-V007T006A019.
[62] Milisavljevic-Syed, J., Allen, J. K., Commuri, S., and Mistree, F., 2020, Adaptable Concurrent Realization of Networked Engineering Systems (ACRONES).

[63] Ahmad, S., Wong, K. Y., Tseng, M. L., and Wong, W. P., 2018, "Sustainable product design and development: A review of tools, applications and research prospects," Resources, Conservation and Recycling, 132, pp. 49-61.
[64] Rocha, C. S., Antunes, P., and Partidário, P., 2019, "Design for sustainability models: A multiperspective review," Journal of Cleaner Production, 234, pp. 1428-1445.
[65] Ma, J., and Kremer, G. E. O., 2016, "A systematic literature review of modular product design (MPD) from the perspective of sustainability," The International Journal of Advanced Manufacturing Technology, 86(5), pp. 1509-1539.
[66] Panchal, J. H., Paredis, C. J., Allen, J. K., and Mistree, F., 2009, "Managing Design-Process Complexity: A Value-of-Information Based Approach for Scale and Decision Decoupling," Journal of Computing and information Science in Engineering, 9(2), p. 021005.
[67] Ceschin, F., and Gaziulusoy, I., 2016, "Evolution of design for sustainability: From product design to design for system innovations and transitions," Design Studies, 47, pp. 118-163.
[68] Liu, B., Huang, S., Fan, W., Xiao, T., Humann, J., Lai, Y., and Jin, Y., 2016, "Data driven uncertainty evaluation for complex engineered system design," Chinese Journal of Mechanical Engineering, 29(5), pp. 889-900.
[69] Erkoyuncu, J. A., Roy, R., Shehab, E., and Cheruvu, K., 2011, "Understanding service uncertainties in industrial product–service system cost estimation," The International Journal of Advanced Manufacturing Technology, 52(9), pp. 1223-1238.
[70] Wang, R., Nellippallil, A. B., Wang, G., Yan, Y., Allen, J. K., and Mistree, F., 2019, "Ontology-based uncertainty management approach in designing of robust decision workflows," Journal of Engineering Design, 30(10-12), pp. 726-757.
[71] Zha, X. F., and Du, H., 2006, "Knowledge-intensive collaborative design modeling and support," Computers in Industry, 57(1), pp. 56-71.
[72] La Rocca, G., 2012, "Knowledge based engineering: Between AI and CAD. Review of a language based technology to support engineering design," Advanced engineering informatics, 26(2), pp. 159-179.
[73] Regli, W. C., Hu, X., Atwood, M., and Sun, W., 2000, "A survey of design rationale systems: approaches, representation, capture and retrieval," Engineering with computers, 16(3-4), pp. 209-235.
[74] Schreiber, A. T., Schreiber, G., Akkermans, H., Anjewierden, A., Shadbolt, N., de Hoog, R., Van de Velde, W., Shadbolt, N. R., and Wielinga, B., 2000, Knowledge engineering and management: the CommonKADS methodology, MIT press.
[75] Muster, D., and Mistree, F., 1988, "The decision support problem technique in engineering design," International Journal of Applied Engineering Education, 4(1), pp. 23-33.
[76] Hatchuel, A., and Weil, B., 2009, "CK design theory: an advanced formulation," Research in engineering design, 19(4), p. 181.
[77] Mistree, F., Smith, W., Bras, B., Allen, J., and Muster, D., 1990, "Decision-based design: a contemporary paradigm for ship design," Transactions, Society of Naval Architects and Marine Engineers, 98, pp. 565-597.
[78] Allen, J. K., Seepersad, C., Choi, H., and Mistree, F., 2006, "Robust design for multiscale and multidisciplinary applications," Journal of Mechanical Design, 128(4), pp. 832-843.
[79] Chen, W., Allen, J. K., Mavris, D. N., and Mistree, F., 1996, "A concept exploration method for determining robust top-level specifications," Engineering Optimization+ A35, 26(2), pp. 137-158.
[80] Choi, H. J., Mcdowell, D. L., Allen, J. K., and Mistree, F., 2008, "An inductive design exploration method for hierarchical systems design under uncertainty," Engineering Optimization, 40(4), pp. 287-307.
[81] Hou, L., and Jiao, R. J., 2020, "Data-informed inverse design by product usage information: a review, framework and outlook," Journal of Intelligent Manufacturing, 31(3), pp. 529-552.
[82] Milisavljevic-Syed, J., Allen, J. K., Commuri, S., and Mistree, F., 2020, "Architecting Networked Engineered Systems."
[83] Milisavljevic, J., Commuri, S., Allen, J.K. and Mistree, F., 2017, "Concurrent Design Exploration Method (CDEM) of Networked Engineering Systems," ASME International Design Engineering Technical Conferences, ASME, Cleveland, Ohio.
[84] Jin, J., and Shi, J., 1999, "State space modeling of sheet metal assembly for dimensional control," Journal of Manufacturing Science and Engineering, 121(4), pp. 756-762.

[85] Ding, Y., Ceglarek, D., and Shi, J., 2002, "Design evaluation of multi-station assembly processes by using state space approach," Journal of Mechanical Design, 124(3), pp. 408-418.